Price risk management effect on the China's egg "Insurance + Futures" mode: an empirical analysis based on the AR-Net model

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Abstract

Egg prices are linked to people's livelihoods, and layer farmers face the risk of large fluctuations. The "Insurance + Futures" mode, as one of new price risk management modes, suffers from the problems of inaccurately determining insurance price and premium rate: an approach that overcomes these problems by proposing a mode based on the autoregressive neural network(AR-Net) model is proposed. This study uses the data pertaining to China's egg futures closing prices from November 2013 to March 2021 for analysis, a dataset of 1756 samples can be obtained from the Wind database. The improved egg price risk management mode presented herein comprises three stages. Firstly, compared with the statistical models (Autoregressive model, ARIMA model, Monte Carlo simulation) and neural network model (Back propagation (BP) model, convolutional neural network (CNN) model), the AR-Net model improves the accuracy of insurance price forecast by its seasonal trend coefficients. Secondly, the AR-Net model is used for rolling forecasts of insurance price and premium rate during the insurance period. Scenario simulations predict that the new mode offers better risk management. Thirdly, the result of robustness analysis by value at risk-generalized autoregressive conditional heteroskedasticity(VaR-GARCH) model implies that the AR-Net model can improve the management of risk.

Keywords: AR-Net model; egg price; price risk management mode; scenario simulation; time series rolling forecast

1. Introduction

The outbreak of the COVID-19 has not only caused a profound impact on global economic growth, but also affected the survival of farmers in China. Recently, the risk of price fluctuations in agricultural product market has gradually increased, and the hedging needs of agricultural entities are also rising (Menapace *et al.*, 2016). Some studies (Cole & Xiong, 2017; Yang, 2018; Lv, 2020) have shown that agricultural insurance plays an extremely significant role in reducing income fluctuations and increasing production. There is a long-term co-integration relationship between agricultural insurance and farmers' incomes (Liu *et al.*, 2021), which is one of the most effective risk management modes for farmers.In addition, Winsen *et al.*, (Winsen *et al.*, 2016)found that the attitude to risk among farmers exerts a significant influence on undertaking pre-event and post-event risk management behaviors. Unexpectedly, farmers in China have a strong willingness to manage market risks, but participation in agricultural insurance is extremely rare (An & Fang, 2016). Farmers as the main purchaser of agricultural insurance, the effective demand for agricultural insurance by farmers is obviously insufficient (Bellemare, 2018).This is also the reason why China's agricultural insurance coverage is relatively low, and farmers' ability to resist risks is weak (Cai & Qin, 2017).

Due to the strict futures market access system, and farmers who lack professional knowledge, farmers in China are unlikely to directly use the futures market for risk hedging. The "Insurance + Futures" mode is one of new modes of price risk management. This process of price risk management includes three key steps that can help farmers using futures markets for risk hedging. Firstly, layer farmers buy egg price insurance from insurance companies. Secondly, insurance companies purchase egg put options from futures companies through paying premiums. Thirdly, futures companies hedge the risk of egg price fluctuations in the futures market. The combination of agriculture insurance and futures market may help stabilize egg prices or even increase the income of farmers. All in all, it is essential to improve the risk management effect of this mode.

Currently, neural network models are among those most frequently used as time-series predictors(Ainnur *et al.*, 2021; Livieris *et al.*, 2020; Nawaf *et al.*, 2022). However, in terms of agricultural Price Risk Management mode, researchers usually use the autoregressive (AR) model, the autoregressive integrated moving average (ARIMA) model, and Monte Carlo simulation to determinate insurance prices and premiums (Arash & Younes, 2018; Wu & Qiu, 2021; Yu *et al.*, 2020). These traditional models can fit the linear trend of the time series and exhibit high accuracy in short-term predictions (Contreras *et al.*, 2003). Neural network can better fit price changes and the non-linear trends therein, and can achieve good results in long-term forecasting (Zhang & Lou, 2021). Therefore, ARIMA and back propagation neural network models are used to predict, respectively, the short-term and long-term prices of Yunnan Pu'er tea (Dou *et al.*, 2022). Different from the model mentioned above, Triebe *et al.*, (Triebe *et al.*, 2019) first used the autoregressive neural network (AR-Net) model to predict the daily temperature variations in New Delhi in 2019 to good effect. This interesting research found that the AR-Net model has fewer parameters to be adjusted, and its seasonal trend coefficients can better capture seasonal trends in time series. The egg futures price is used as an insurance price in "Insurance + Futures" mode, this mode requires long-term prediction. Meanwhile, egg futures prices exhibit strong non-linear and seasonal changes. The AR-Net model is used to predict these changes in Section 3.

Researchers use simple indicators such as the amount of profit or loss, or the volatility of returns to measure the risk of the model in the effect of risk management (Wang & Xia, 2021). The Value at Risk (VaR) model is widely used in the evaluation of the effect of financial risks, and it has achieved good results in the stock and foreign exchange markets (Chen *et al.*, 2007; Liu & Chang, 2015). The GARCH-VaR model under the assumption of a t-distribution and GED distribution can better reflect the yield of risk characteristics (Chen & Yu, 2002). Therefore, we examine the risk management effect under a GARCH-VaR model in Section 4.

2. Approach and hypothesis

2.1 AR-Net model

According to Figure 1 and 2, the AR-Net model is a neural network based on the AR model, which takes lag $y_{t-1}, \ldots, y_{t-p}$ as the input and target. The AR-Net model takes the AR model coefficient as the architecture of the neural network, and its node weight are w_1, w_2, ...and w_p corresponding to the AR coefficient in the AR model, which has n hidden layers of size k (Triebe *et al.*, 2019).

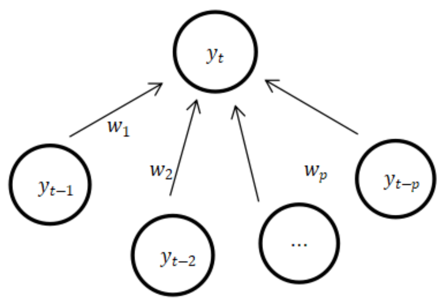

Fig. 1. AR-Net is designed so that the parameters of the first layer are equivalent to AR coefficients

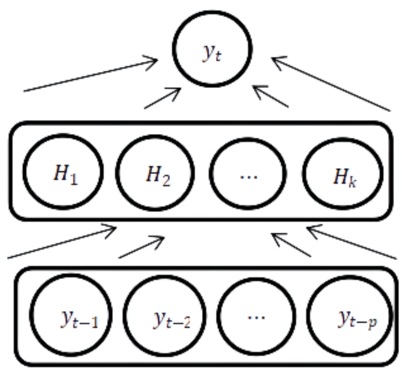

Fig. 2. AR-Net can optionally be extended with hidden layer to achieve better prediction accuracy

The autoregressive (AR) model uses the lag value of time series as predict value for multiple regression, the AR model can predict small sample data with auto-correlation. As one of the traditional statistical models, the AR model is simple and interpretable.

$$y_t = c + \sum_{i=1}^{p} w_i \times y_{t-i} + e_t \tag{1}$$

Where $y_{t-1}, \ldots, y_{t-p}$ are the p lag terms used to predict y_t. The p weights w_i, by which each of the p lags y_{t-i} is multiplied, are also referred to as the AR-coefficients.

The AR-Net model sets small weight parameters to zero in the learning process, while keeping other weight parameters unchanged. The AR-Net model adds a regularization term to the minimized loss L to obtain the real AR order, so the assumption that the AR coefficient must continuously lag becomes less important. The parameters of the AR-Net model mainly include AR coefficient, expected sparseness (s), regularization term (c_λ), regularization intensity (R), and loss term (L), where $c_\lambda \approx \sqrt{\hat{L}}/100$.

$$min_\theta L(y, \hat{y}, \theta) + \lambda(s) * R(\theta) \tag{2}$$

$$\lambda(s) = c_\lambda * (s^{-1} - 1) \tag{3}$$

The regularization curve parameters c_1 and c_2 depend on the range of the AR coefficients. Parameters are processed by the regularization function using a simple square root transformation:

$$R(\theta) = \frac{1}{p} \sum_{i=1}^{p} \frac{2}{1 + \exp(-c_1 * |\theta_i|^{\frac{1}{c_2}})} \tag{4}$$

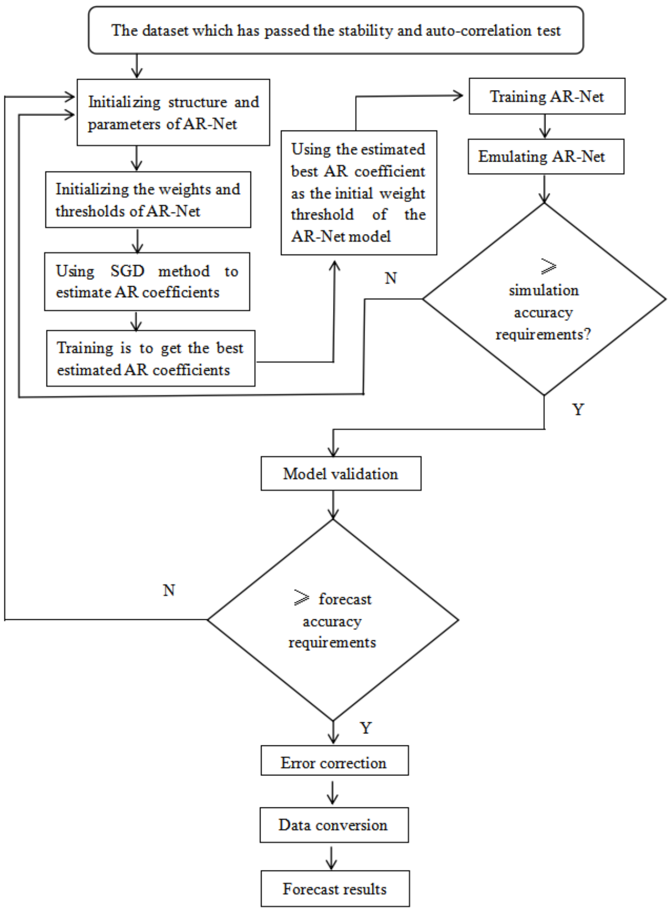

Fig. 3. AR-Net model of egg futures price prediction flowchart

According to Figure 3, firstly, the data which have passed the stability and auto-correlation test are input into the AR-Net model. Then the data will be used to adjust the parameters of the AR-Net model. Moreover, the Stochastic Gradient Descent (SGD) method is employed to adjust these parameters. The adjustment of seasonal trend coefficients includes yearly seasonality, weekly seasonality, and daily seasonality, it is conducive to fit the seasonality of egg prices. Secondly, relevant experience is used to select the hidden layer of the AR-Net model. The regularization method is used to determine the sparseness of the AR-Net model coefficients. Sparseness entails grasping the main characteristics of the time series to improve its ability to generalize. To have a higher generalization ability in other samples, the appropriate learning rate is selected based on experience. Finally, the optimal parameters as the initial weight threshold of the model will be obtained after adjustment. If the predicted data meet the training requirements, parameter adjustment will end. Otherwise, the parameter adjustment will continue. The AR-Net model will output the prediction result after error correction and data conversion.

2.2 Sample data processing

The dataset of egg futures price selects the closing price of China egg futures (active contracts) (unit: yuan/500 kg); egg spot price selects the national average egg trade price (unit: yuan/50 kg); these data are all taken from the Wind database. For egg futures and spot price data, excluding holidays, egg futures with data but egg spot prices without data, or egg spot prices with data but egg futures without data a total of 1756 sets of egg futures and spot price data are matched. To test the effect of the price prediction model, the effective dataset is divided into a training set (November 18, 2013 to December 31, 2018), a verification set (January 2, 2019 to December 31, 2019), and a test set (March 9, 2020 to March 11, 2021). The number of items in each set is 1259, 245, and 252, respectively. The training set is used for model training, the verification set is adopted to test the results of model training, and the test set is employed to test the price prediction effects of different models. Data missing value and abnormal value processing: firstly, missing and abnormal values are detected and filled into the missing data using Equation (5), and the abnormal data are replaced by a mean smoothing method, as given by Equation (6).

$$x_{a+i} = x_a + \frac{i(x_{a+j} - x_a)}{j} \tag{5}$$

$$x_b = (x_{b+i} + x_{b-i})/2 \tag{6}$$

Where x_{a+i} is the missing value at time $a + i$; x_b is the outlier value at time b; x_b, x_{a+j}, and x_{b-i} are respectively the valid data at period a, $a + j$, $b + i$ and $b - i$.

It is found that the raw dataset is unstable after ADF testing, making it necessary to take the logarithm, then the first order difference of the dataset. The ADF test results are listed in Table 1:

Table 1. The results of the ADF test of egg futures prices

Sample interval		ADF value	P-value	1%	5%	10%	DW value	Correlation
Full sample	lnF	-0.5950	0.8692	-3.4339	-2.8630	-2.5676	0.0271	Positive
	ΔlnF	-42.9839	$\leq$ 0.0001	-3.4340	-2.8630	-2.5676		
Training set	lnF	-2.6640	0.0807	-3.4353	-2.8636	-2.5679	0.0220	Positive
	ΔlnF	-36.2534	$\leq$ 0.0001	-3.4354	-2.8636	-2.5680		
Validation set	lnF	-1.9774	0.2969	-3.4436	-2.8673	-2.5699	0.0341	Positive
	ΔlnF	-22.7814	$\leq$ 0.0001	-3.4437	-2.8673	-2.5699		
Test set	lnF	0.1099	0.9659	-3.4599	-2.8744	-2.5737	0.0368	Positive
	ΔlnF	-17.1052	$\leq$0.0001	-3.4563	-2.8729	-2.5729		

According to the ADF test in Table 1, the egg futures data don't pass the stationary test at the 5% level of significance, but after first-order difference processing, the ADF value of the data is less than the critical value of the 1% level of significance, and the p-value is close to 0, which passes the stationary test at the 1 % level of significance.This proves that the time series data of egg futures price treated by logarithm and first-order difference are stable.

2.3 Hypothesis

Two key research issues are further discussed, and two hypotheses are verified:

Firstly, the AR-Net model can learn from real AR coefficients, solving long-term data dependence, and minimize the mean square prediction error (MAE). For the first time, to improve the effectiveness of the risk management mode, we use the AR-Net model to predict egg futures prices. Based on this, Hypothesis 1 is proposed: compared with traditional statistical models and neural network models, the AR-Net model is more accurate in predicting egg target prices.

Secondly, if the AR-Net model can provide a more accurate prediction, then the predicted price will be used to determine the insurance price and premium rate. Moreover, a reasonable insurance price will control the risk of egg price fluctuations within a certain range, which can help farmers earn a more stable income. Accordingly, Hypothesis 2 is proposed: compared with the traditional “Insurance + Futures” mode and agricultural price insurance, the egg “Insurance + Futures” mode based on the AR-Net model has a better risk management effect.

3. Result of empirical analysis

3.1 Prediction of target price based on AR-Net model

Figure 4 charts the prediction of the egg futures closing price when using the AR-Net model. The AR-Net model is optimized by the parameters of the sample training set (November 18, 2013 to December 31, 2018) and the verification set (January 2, 2019 to December 31, 2019). According to Figure 4, the closing price data of egg futures from November 18, 2013 to December 31, 2018 are actual time series data, and the data from January 2, 2019 to December 31, 2019 are the closing price data of egg futures predicted by the AR-net model. To improve the accuracy and rationality of the prediction results, k-fold cross validation is used on the dataset.

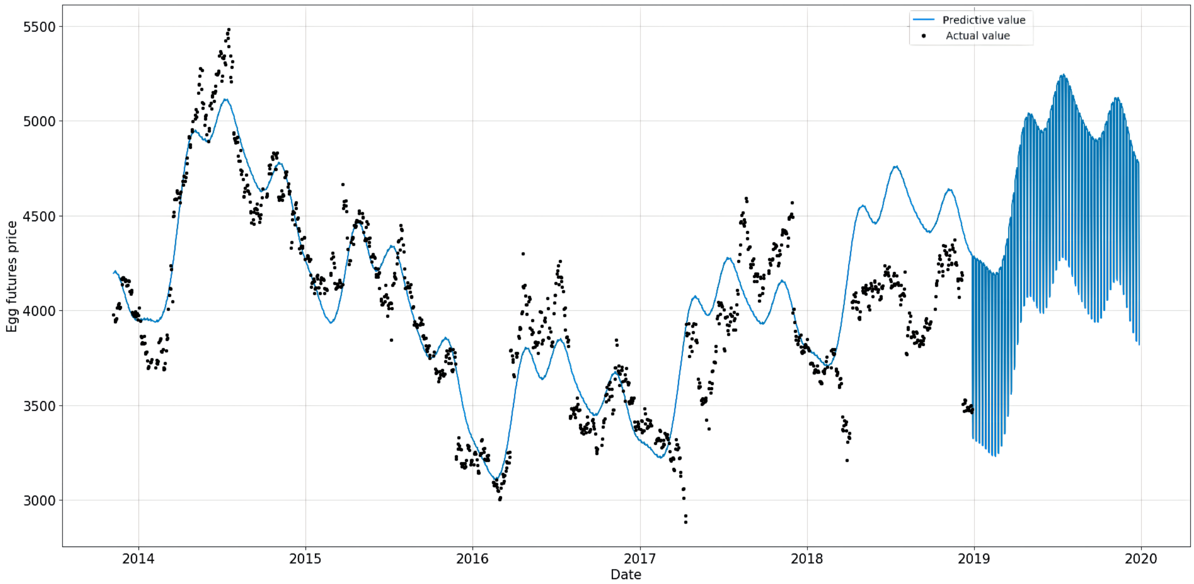

Fig. 4. One-year egg futures price predictions based on the AR-Net model

To compare the prediction effect of the price model, scholars always use MAE and root mean square error (RMSE) as indicators as the evaluation indicators to estimate the accuracy of the model’s predictions (Liu *et al.*, 2021). The MAE, RMSE and decision coefficient (R^2) are used to evaluate the accuracy of the model. The model with better comprehensive performance of the three indices will be selected as the optimal price prediction model. The calculation is as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \tilde{y_i}| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|y_i - \tilde{y_i}|} \tag{8}$$

$$R^2 = \frac{\sum_{i=1}^{N}[(y_i - \bar{y_i})(y_i - \tilde{y_i})]^2}{\sum_{i=1}^{N}(y_i - \bar{y_i})(\tilde{y_i} - \hat{y_i})} \tag{9}$$

Where N is the number of predicted values; y_i represents the true value; $\tilde{y_i}$ is the predicted value; $\bar{y_i}$ is the average of the true values;$\hat{y_i}$ denotes the average of the predicted values.

Table 2. Egg futures model prediction error analysis

Model	MAE	RMSE	R^2
AR model	2.74	8.31	0.5329
ARIMA model	2.64	8.04	0.5637
Monte Carlo simulation	2.84	9.47	0.6674
AR-Net model	1.42	4.32	0.8919
CNN model	1.53	4.86	0.8261
BP model	1.69	5.28	0.7825

To select the optimal price prediction model, firstly, according to the analysis of the MAE and RMSE indicators in Table 2, the MAE (1.42) and RMSE (4.32) of the AR-Net model are the smallest, indicating that AR-Net model has the highest accuracy in predicting the price of egg futures among these models. Secondly, it is found that the AR-Net model is 0.8919 of R^2, which is the highest, indicating that the AR-Net model also has a strong advantage in fitting egg futures price.

In summary, compared with these prediction models, the AR-Net model provides the best predictions. This verifies Hypothesis 1: compared with traditional statistical models and neural network models, the AR-Net model is more accurate in predicting egg target prices. Therefore, it is speculated that the AR-Net model can better simulate and predict the price of egg futures in the "Insurance + Futures" mode. The AR-Net model can then be adopted to predict insurance prices.

3.2 Premium calculation in the "Insurance + Futures" mode

In the egg "Insurance + Futures" mode, farmers transfer the risk of a future egg price decline to the insurance company by paying a premium to their chosen insurance company. The average closing price of egg futures predicted by the AR-Net model is compared with the average market price of eggs in the spot market, and we will take the lower price as the insurance price. In this egg price risk management mode, the cost-benefit to farmers is affected by insurance price: if the settlement price exceeds the insurance price, the insurance company will not compensate for this. The cost of farmers is a premium expenditure, and the income is a spot-market income; if the settlement price is lower than the insurance price, the insurance company will compensate farmers. The cost to the farmers is the expenditure on the premium, and any loss of income will be compensated by the insurance company.

Regarding the determination of premiums, Monte Carlo simulation, Copula model, and HP filtering method are usually used to determine premiums (Rejesus *et al.*, 2006; Niu & Chen, 2016). Therefore, we will determine the premium rate according to the egg futures price during different insurance periods, and premium rates are obtained by price fluctuations. In related research results, Blair *et al.*, (Blair *et al.*, 2001) shows that the weighted BS implied volatility method can eliminate the deviation caused by the volatility smile. Using different call and put options can increase the amount of information and eliminate the measurement error caused by the clientele effect. When calculating the premium, it is necessary to modify the implied volatility of options. Corn and soybean meal futures options are the main components of chicken feed. There is a certain correlation between changes in corn and soybean meal futures prices and egg futures prices (Zheng *et al.*, 2018). Therefore, the historical data of implied volatility of corn and soybean meal futures options are employed to correct the volatility.

First, to calculate the premium, the implied volatility needs to be calculated. The implied volatility is most suitable to represent the market's volatility expectations for the return of the underlying asset over time in the future. Therefore, the Black-Scholes (B-S) model is used to address the implied volatility. When C, S, K, and T are known, the implied volatility of egg futures price can be obtained through the inverse solution of the B-S option pricing model:

$$C = S \times N(d_1) - Ke^{-rT}N(d_2) \tag{10}$$

$$d_1 = \frac{ln\frac{S}{K} + (r + 0.5\sigma^2)T}{\sigma\sqrt{T}} \tag{11}$$

$$d_2 = \frac{ln\frac{S}{K} + (r - 0.5\sigma^2)T}{\sigma\sqrt{T}} \tag{12}$$

Where C is the initial price of the option; K represents the price at the time of option delivery; S is the current price of financial assets, T denotes the option validity period, r_f is the risk-free interest rate calculated by continuous compound interest, and σ^2 is the annualized variance, where $N()$ represents the cumulative probability distribution function ($\frac{1}{\sqrt{2\pi}}\int_{-\infty}^{d_n} e^{-\frac{x^2}{2}}$) of normally distributed variables.

The calculated implied volatility is weighted, and the four implied volatility required for weighting can be recorded as σ_H^C, σ_L^C, σ_H^P, and σ_L^P, respectively. Where C and P represent call and put options respectively, and H and L represent higher and lower exercise prices respectively. Firstly, we calculate the average of the implied volatility of call and put options with the same exercise price, and then weight the options with different exercise prices using a linear interpolation method to obtain the implied volatility:σ_H which is the implied volatility of options with a higher exercise price, and σ_L denotes the implied volatility of options with a lower exercise price.

According to the analysis (Gao *et al.*, 2021), soybean meal has a low proportion in layer feed, so it is not fully reflected in egg futures prices. Therefore, the implied volatility of corn futures options is employed to correct the implied volatility of egg futures options. The unit net premium is calculated according to the unit insurance amount and the egg futures price thus simulated and predicted by the AR-Net model.

The unit net premium is calculated according to the unit insurance amount and the egg futures price is simulated and predicted by the AR-Net model:

$$D_i = (\frac{t_i}{n}\beta\sigma * E_i)^2 \tag{13}$$

$$\sigma_i = ln(\frac{D_i}{E_i^2} + 1) \tag{14}$$

$$\mu_i = ln(E_i) - \frac{\sigma_i^2}{2} \tag{15}$$

$$P_{net} = \frac{1}{Q} * \frac{\sum_{i=1}^{3} \exp(-r_f * t_i) * \sum_{j=i}^{n} max(E_i - S_{ij}, 0)}{n} \tag{16}$$

Where n represents the number of simulated egg prices, G_i is the insured proportion of the i-th insurance period, Q denotes the number of insurance periods, P_{net} is the unit net premium, r_f is the risk-free interest rate (we used the average annualized Shibor interest rate in 2020 is used), E_i is the unit insurance amount (we used the three-day average of the closing price in the settlement period is used), and D_i is the standard deviation of the futures price, σ_i and μ_i are respectively the standard deviation and mean value of log-normal distribution corresponding to the closing price of the i-th underlying contract, and S_{ij} denotes the price of the underlying contract corresponding to the i-th settlement date.

Finally, we multiply the net premium per unit by the cost factor to obtain the total premium per unit. The cost factor refers to the various additional costs involved in insurance, including the insurance company's business costs, commission expenses, estimated profits, and security fees. This research combines the characteristics of eggs with transportation costs, storage costs, and wastage of perishable eggs, assuming the additional costs (α) are 10% of the net premium.

$$P = \alpha \times P_{net} \tag{17}$$

On the premise that the insurance ratio is 100% and the maximum amount insured is 50 tons, the unit net premium, unit total premium and rate of egg futures price insurance are calculated (Table 3). As a convolutional neural network (CNN) provides a good price-prediction result, we will use the CNN model in egg price risk management mode.

Table 3. Premium simulation of egg prices in the insurance period

Number of periods	Phase1	Phase2	Phase3	Average
"Insurance + Futures" mode based on AR-Net model				
Unit insurance amount	7.064	5.568	6.778	6.47
Unit insurance amount(yuan/kg)	0.327	0.234	0.296	0.336
Unit total premium(yuan/kg)	0.363	0.261	0.329	0.797
Insurance rate(%)	5.14	4.69	4.85	4.89
"Insurance + Futures" mode based on CNN model				
Unit insurance amount	7.245	5.214	6.981	6.48
Unit insurance amount(yuan/kg)	0.334	0.257	0.313	0.301
Unit total premium(yuan/kg)	0.371	0.286	0.348	0.335
Insurance rate(%)	5.26	4.73	4.96	4.98
Traditional agricultural price insurance				
Unit insurance amount	9.872	7.623	8.412	8.636
Unit insurance amount(yuan/kg)	0.457	0.353	0.389	0.399
Unit total premium(yuan/kg)	0.412	0.388	0.428	0.409
Insurance rate(%)	5.67	5.23	4.98	5.29

3.3 Price risk management effect on the "Insurance + Futures" mode under the price prediction of AR-Net model

Generally, farmers will choose a period when egg prices fluctuate significantly as an insurance period to avoid the risk of egg price fluctuations. Sample data with large fluctuations are selected from the historical dataset of egg spot price.

According to Figure 5, the heat map reflects the price month-on-month volatility ratio of the egg spot price. In the heat map, green denotes higher prices, red denotes lower prices, and white represents prices that are at an intermediate level. If the color is darker, the price changes will be more extreme.Farmers are vulnerable to loss in the four months of March, June, July, and November. Especially at the end of June and the beginning of July each year, egg spot prices have fallen sharply. The basis of egg futures has significantly expanded after 2018. Therefore, the risk of falling egg price during insurance period must be managed as a matter of urgency.

Accordingly, in this section, we describe a simulated risk-management scenario is described. Setting an egg insurance period starting in March 2020 as an example, the insurance period is set to one year. The insurance period is divided into three phases (each of four months), and the settlement dates are July 2020, and November and March 2021.

The actual historical price in the past four months is used as the sample dataset to predict the price of settlement month. Since the actual price datum of egg futures in every month is about 20. Therefore, 20 data items in the settlement month are predicted and the average value is taken as the settlement price. It is assumed that layer farmers are insured for 50 tons in each settlement period (the maximum insured output in each period), and the total insurance ratio is 100 %, and the egg futures are simulated and predicted by using the proposed price prediction model. In addition, government subsidies and other expenses in insurance period are not considered.

Date	2013	2014	2015	2016	2017	2018	2019	2020
January		8. 46	9. 24	8. 45	6. 72	9. 14	8. 75	8. 95
February		8. 02	9. 07	8. 36	5. 88	9. 10	7. 74	7. 11
March		8. 07	8. 30	7. 20	5. 56	7. 71	7. 09	6. 93
April		8. 62	7. 61	7. 23	5. 59	7. 54	7. 78	7. 07
May		9. 91	7. 41	7. 27	5. 10	7. 78	8. 97	6. 63
June		9. 38	7. 18	7. 12	5. 62	7. 72	8. 49	6. 39
July		9. 91	7. 19	6. 88	6. 00	7. 64	9. 24	6. 87
August		10. 75	8. 52	7. 30	8. 06	9. 34	10. 17	8. 14
September		11. 15	9. 06	8. 16	8. 99	9. 77	11. 31	8. 34
October		10. 51	7. 90	7. 44	8. 15	8. 93	11. 04	7. 84
November	8. 29	10. 32	7. 84	7. 46	8. 40	9. 01	10. 92	7. 68
December	8. 34	9. 95	8. 02	7. 15	9. 10	8. 76	9. 70	7. 99

Fig. 5. The volatility of egg spot prices in each month between 2013 to 2020

Three insurance designs are set for common risk management scenarios in this part. Insurance settlement months include July 2020, November 2020, and March 2021. If settlement price is lower than the insurance price, the insurance company will compensate the farmers; if the settlement price exceeds the insurance price, the settlement will be used as insurance price, the cost to the farmers is the premiums.

(1) The egg "Insurance + Futures" mode based on the AR-Net model

The insurance price is the average closing price of egg futures predicted by the AR-Net model during the insurance period. The settlement price is the average price of egg futures in the insurance settlement months. The egg "Insurance + Futures" mode based on CNN model insurance policy design is similar to the mode based on the AR-Net model, but the insurance price is predicted using the CNN model.

(2)Egg traditional agricultural price insurance

The insurance price is the average price of egg spot in last year same period (March 2019-March 2020). The settlement price is the average spot price in the settlement month.

(3) Not involved in risk management

The selling price is the average egg spot prices in the settlement month.

The premium rates of the three phases are used in the various modes of risk management to calculate the profit. To evaluate the influence of the "Insurance + Futures" mode on the income of farmers, the mode is assessed by two indicators of poultry-breeding income and income risk ratio, and the two indicators are tested. The income index of poultry breeding reflects the income of such farmers: the income risk ratio index not only considers the income, but also reflects the price fluctuation risk (the Income risk ratio = yield / volatility).

Among them, the calculation formula of the yield is:

$$\mu_i = ln(\frac{S_i}{S_{i-1}}) \tag{18}$$

The formula for calculating the volatility is:

$$\delta = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\mu_i - \bar{\mu})^2}}{\sqrt{\tau}} \tag{19}$$

Where μ_i is the rate of return of the ith period (i = 1, 2, 3, . . . , n; n = 20), S_{i-1}, S_i are the settlement prices of period $i-1$ and i, respectively, $\bar{\mu}$ is the rate of return Mean, τ is the length of the event interval.

Income risk ratio is adopted to test whether the risk management effect of the "Insurance + Futures" mode based on the AR-Net model is better than other modes of risk management.

Table 4. Income and risks of farmers under different simulation scenarios

Mode	Number of periods	Layer breeder income (yuan)	Premium (yuan)	Total income (yuan)	Total income after deducting premiums (yuan)	Yield/ volatility	Average rate of return/ volatility
"Insurance + Futures" Mode based on the AR-Net model	Phase1	420500	21613.70	1213900	1154399	29.23	27.58
	Phase2	370500	17376.45			25.98	
	Phase3	422900	20510.65			27.54	
"Insurance + Futures" Mode based on CNN model	Phase1	424300	22312.92	1200100	1140147	27.21	25.94
	Phase2	365200	17273.96			24.43	
	Phase3	410600	20365.76			26.17	
Egg traditional agricultural price insurance	Phase1	384700	19773.58	1177600	1115325	25.61	22.28
	Phase2	390800	18328.52			20.83	
	Phase3	402100	19501.85			20.39	
Not involved in risk management	Phase1	312700	/	1105600	1105600	15.76	18.99
	Phase2	390800				20.83	
	Phase3	402100				20.39	

Compared with different risk management modes (Table 4), and under the background of the rapid growth in egg prices at the beginning of 2021, the yield / volatility of the "Insurance + Futures" mode based on the AR-Net model is better in terms of three-stage income, the net income is 1,154,399 yuan, exceeding that under other modes. Moreover, the premium rate of the AR-Net model is lower, thus reducing the cost of insurance. The average rate of return / volatility of the AR-Net model is the highest, reaching 27.58; this is much higher than under other modes, that shows the "Insurance + Futures" mode based on the AR-Net model can play a prominent role in stabilizing incomes and fluctuating egg prices.

According to above data and analysis thereof, it is verified that, compared with other risk-management modes, participating in the "Insurance + Futures" mode based on the AR-Net model can protect farm incomes and reduce the risk caused by egg price fluctuations. Hypothesis 2 is further validated.

4. Robustness analysis

Here, the risk management effect is tested by the VaR-GARCH model. This is also conducive to analysis of the robust results of the risk-management effect. VaR is a widely used risk indicator in the financial industry, which represents the value of assets considering risk. Let the random variable describing portfolio loss be x, the probability distribution function be $f(x)$, and the confidence level be α, the standard mathematical expression for this is:

$$VaR(\alpha) = inf\left\{x|f\left(x\right) \geq \alpha\right\} \tag{20}$$

Where x is normally distributed. VaR has been widely applied in financial derivatives risk management. The main calculation steps of VaR model are described as follows:

Compared with the rate of income, the logarithmic rate of return has good statistical characteristics and is more suitable for financial modelling. Therefore, here, we take the logarithm of the daily closing price series of egg futures (active). The logarithmic rate of return is given by:

$$R_t = lnP_t - lnP_{t-1} \tag{21}$$

Where, lnP_t and lnP_{t-1} are the egg futures prices in period t and period $t-1$.

As the GARCH model can better fit the characteristics of a "peak and thick tail" in the distribution of daily return series, researchers usually use VaR-GARCH models to measure the risk of egg price fluctuations. Therefore, a GARCH (p, q) model is used to estimate the volatility in the settlement price. The optimal lag order of the model is determined by AIC and SC criteria, we find that GARCH (1,1) model is the most appropriate. The VaR is given by:

$$VaR = \mu - Z_{\alpha} \tag{22}$$

Where α is the confidence interval, σ denotes the settlement price volatility, μ is the insurance value, and Z_{α} is the lowest value of the asset portfolio at a given confidence level.

Table 5. VaR-GARCH estimation results of three modes under different confidence intervals

Risk management model		GARCH coefficient	GARCH Std.error	GARCH Z-statistic	GARCH prob	Confidence level(VaR) 95%	97%	99%
"Insurance + Futures" Model based on AR-Net model	C	-2.75E-05	7.69E-05	-0.357541	0.7207	46108	46239	46485
	RESID (-1)^2	0.880988	0.376717	2.338593	0.0019			
	GARCH (-1)	0.441288	0.053325	8.275489	$\leq$ 0.0001			
"Insurance + Futures" Model based on CNN model	C	-3.24E-05	6.75E-05	-0.417012	0.7248	47864	47991	48013
	RESID (-1)^2	0.854066	0.393317	2.171442	0.0016			
	GARCH (-1)	0.418744	0.0113344	6.003221	$\leq$ 0.0001			
Traditional price insurance	C	-3.15E-05	6.67E-05	-0.48588	0.6944	49508	49639	49885
	RESID (-1)^2	0.7648	0.08471	7.5554	0.00106			
	GARCH (-1)	0.2552	0.01386	0.021711	$\leq$ 0.0001			
Without risk management	C	0.001723	0.001212	1.421008	0.1553	51594	51751	52048
	RESID (-1)^2	1.4123	0.3512	3.95495	0.0001			
	GARCH (-1)	0.13268	0.339771	-0.30934	0.0174			

According to Table 5, the test dataset covers the time from March 10, 2020 to March 10, 2021, the VaR-GARCH model can accurately measure the risk of various modes, and it can readily reflect the risk associated with each mode of risk management. Furthermore, when the confidence levels reach 95%, 97%, and 99%, the maximum loss of improved egg price risk management mode based on the AR-Net model is less than that under other modes, thus supporting Hypothesis 2.

5. Conclusions and inspiration

Based on the advanced price prediction model (AR-Net), the validity of the price prediction based thereon is verified. Furthermore, different risk management scenarios are simulated to evaluate the price risk management effect on the "Insurance + Futures" concept, which can enrich the quantitative research methods focused on the "Insurance + Futures" concept and broaden the existing research boundary. Through the above analysis, the following results can be obtained: firstly, compared with other methods that scholars used in the "Insurance + Futures" mode: such as Monte Carlo simulation, AR, ARIMA, and BP or CNN neural network models, the AR-Net model has a strong advantage in the price prediction of egg futures, and we can then obtain more accurate insurance prices. Secondly, when using AR-Net model to calculate premium rates, the chosen mode can achieve better risk-management result. This proves that the AR-Net model can better fits the seasonal trend in egg prices and the changes thereof. Compared with other neural network models, the AR-Net model requires fewer parameters to be adjusted and has a stronger ability to generalize. The insurance price based on the AR-Net model is more accessible to poultry farmers' expectations, which will achieve the purpose of stabilizing incomes and realizing optimal risk mitigation. It is also proved, in the robustness analysis, that the mode based on the AR-Net model can help reduce the extreme risk to poultry farmers.

In summary, the AR-Net model improves the accuracy of insurance price prediction, stabilizes the income of poultry farmers, improves the farmers' ability to manage the risk of egg price fluctuations: it is also conducive to insurance companies in their quest for a rational determination of pricing around insurance policies. The determination of insurance price and premium when using the AR-Net model can reduce unnecessary claims and balance the distribution of benefits between policyholders and insurance companies. This will increase the enthusiasm of insurance companies to participate in egg price risk management, instead of just relying on government subsidies to increase the participation of insurance companies, which will help the long-term development of the "Insurance + Futures" mode. In addition, accurate egg futures price forecasts are also conducive to futures companies hedging risks.

However, there are also many problems in the "Insurance + Futures" mode. Firstly, many farmers in China have a weak awareness of risk management methodologies and there is a prevailing lack of understanding of the modes of risk management with respect to egg prices. In addition, the development of agricultural insurance in China is, as yet, imperfect and there is a lack of appropriate insurance products. Secondly, China's insurance companies cannot directly participate in the futures and option market for trading purposes. Although insurance companies can hedge the risk of price decline through over-the-counter put options and better manage the price risk with the help of the market experience of professional traders, the option fee that insurance companies need to pay is much higher than the cost of entering the futures market to hedge the risk. Insurance companies need to balance the premium income they can earn with the higher option fee charged by futures companies, which is likely to become an important factor affecting the enthusiasm of insurance companies to run pilot schemes in the future. Finally, the investor structure being dominated by retail investors restricts the space and liquidity of risk aversion provided by the futures market, which limits the function of risk management of the "Insurance + Futures" mode.

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