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Price Interval Estimation and Empirical Analysis of the Hog Futures Market Based on the Hidden Markov Model

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Abstract: *In recent years, the live hog futures market has exhibited strong volatility due to multiple factors. However, existing research has paid little attention to price interval estimation and market state transition characteristics, making it difficult to provide effective guidance for market participants. As a direct determinant of pork prices, the futures price of live hogs is of significant economic importance to market participants. This paper analyzes key indicators such as the pig-grain ratio and the inventory of breeding sows based on macro data related to live hogs from 2021 to 2024. The results show that the production capacity of live hogs has been well controlled, the advantage of imported pork has faded, the price of piglets has stabilized and increased, and the industry is approaching a supply-demand balance. Using the Hidden Markov Model(HMM) to analyze daily trading data of live hog futures, this paper sets the number of hidden states to 3, corresponding to the states of "windfall profit," "normal profit," and "thin profit." It calculates the average pig-grain ratio and price under different states. The study ultimately estimates that the futures price interval for a supply-demand balance in the live hog market is 17 to 21.75 yuan, corresponding to a pig-grain ratio interval of 5.82 to 7.77. The results indicate that periods of substantial profit in the live hog industry are closely related to seasonal increases in market demand, supply chain fluctuations, policy adjustments, and international market dynamics.*

Keywords: *Hidden Markov Model, Pig-Grain Ratio Live, Hog Futures Market, Live Hog Production Capacity Control*

1. Introduction

As one of the most important agricultural futures products in China, the price trend of live hog futures significantly impacts the production enthusiasm and income of hog farmers, as well as the consumption expenditure and quality of life of residents[1]. The live hog futures market is highly volatile, influenced by multiple factors such as "black swan events" and changes in the international trade environment. This volatility makes it challenging for market participants to identify reasonable trading opportunities. Existing research on agricultural futures price forecasting primarily focuses on point prediction, with limited emphasis on price interval estimation[2]. Additionally, few studies consider the impact of market state transitions on price formation, failing to fully capture the dynamic nature of the market.

This study aims to address these gaps by employing the Hidden Markov Model (HMM) to analyze the price dynamics of live hog futures. The goal is to provide a more comprehensive understanding of market state transitions and their impact on price fluctuations, thereby offering practical tools for market participants to better grasp trading opportunities[3]. The significance of this research lies in enriching the theoretical framework for agricultural futures price forecasting and providing decision-making support for both policymakers and market participants.

The key innovation of this study is the application of the HMM to model the price of live hog futures, which overcomes the limitations of traditional point prediction methods. By identifying distinct market states and their transitions, this approach offers a more accurate reflection of the market's dynamic characteristics. The collects study and preprocesses macroeconomic and live hog futures market data, select key variables influencing the price of live hog futures, and conducts descriptive and qualitative analyses to identify potential macroeconomic factors. The time-series characteristics of the data are analyzed to capture patterns and trends, and the HMM is used to model price changes under different market states. The results are then evaluated for their predictive ability and applicability.

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2. Data Source and Preprocessing

The data used in this study is sourced from the futures market data provided by Tongdaxin Futures Trading Platform https://www.tdx.com.cn/ and the hog-specific data jointly released by the Ministry of Agriculture and Rural Affairs, National Development and Reform Commission, Ministry of Commerce, General Administration of Customs, and National Bureau of Statistics https://www.moa.gov.cn/.

In establishing the predictive model, this paper selects the closing price as a key reference indicator to more accurately depict the future trend of the main pork futures prices. The variables chosen include the pig-grain price ratio and the per-head output value of live hogs from small-scale and large-scale farming, which reflect the economic benefits of the breeding industry.

2.1 Daily Return Rate Conversion of Market Data

This paper first cleans the data and fills in missing values, then introduces the daily return rate of live hog futures to more precisely capture the short-term price fluctuations in the market. By calculating the daily return rate, which is the percentage change between the settlement prices of the previous day and the next day, we can quickly perceive the subtle changes in price volatility. This reflects the potential relative gains or losses that investors holding the futures contract might realize from one day to the next. The specific formula for the daily return rate is as follows,

$$r_i = \frac{p_{i+1} - p_i}{p_i} \tag{1}$$

Here, r_i represents the daily return rate of the futures on day i and p_i is the settlement price on the day.

2.2 Descriptive Statistical Analysis

Since the data under the categories of "price" and "cost and revenue" are both regular, starting from March 2021 and ending in February 2024, descriptive statistical analysis was conducted on the data under these two categories. Using Python, descriptive statistics were calculated for all variables under these two categories, yielding the results shown in Table 1. Specifically, Variable 1, Variable 2, Variable 3, Variable 4, and Variable 5 represent the national sales price of two-way hybrid sows, the national piglet price, the national ex-farm price of live hogs, the national wholesale market price of pork carcasses, and the wholesale market price of pork carcasses in 36 major and medium-sized cities, respectively.

Table 1. Descriptive Statistics of "Price" and "Cost and Revenue" Indicators (Partial)

Variable	Minimum	Maximum	Mean	Standard Deviation	Variance	Skewness	Kurtosis
1	32.71	71.57	40.76	8.98	80.64	2.09	3.97
2	23.22	87.18	36.59	13.73	188.51	2.01	4.59
3	13.34	27.39	17.32	3.80	14.43	1.26	0.39
4	18.20	34.16	23.27	4.54	20.65	1.15	0.10
5	17.77	34.45	22.82	4.51	20.35	1.26	0.44

The calculation results show that during the period from March 2021 to February 2024, the maximum values of the variables under the "price" indicator generally far exceeded their mean values, forming a typical long-tailed distribution. The positive skewness values further confirmed the extension of the right tail of the data, which not only reflected the instability of the market structure but also implied the possibility of extreme fluctuations. In terms of "cost and revenue," both the output value, cost, and net profit of live hogs from small-scale and large-scale farming exhibited significant fluctuations. It is particularly noteworthy that from January 2023 to January 2024, the net profit of live hogs from both small-scale and large-scale farming remained negative[3]. This phenomenon was directly related to the continuous decline in pork prices in 2023. The decrease in prices meant a reduction in sales revenue, while the breeding costs, such as feed and epidemic prevention, remained unchanged or even increased, severely compressing the net profit of hog farmers. The long-term low prices may have originated from factors such as oversupply in the market and changes in consumer demand. This downturn in the pork market not only reflected the challenges of the current economic environment but also suggested that the future market may need to adapt to and adjust the breeding industry model, cost control strategies, and even consumer habits.

Under the “price” indicator, some variables are closely linked to the final pork prices and influence the trend of pork prices. The trends of the variables under the “price” indicator are shown in Figure 1.

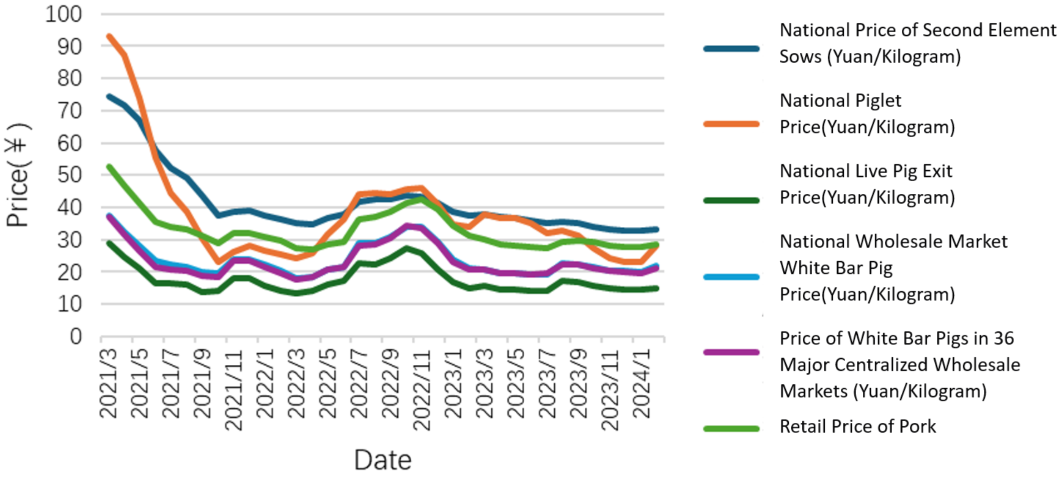

Figure 1. Trend Chart of Variables under the “Price” Indicator

Due to the consistent trends in the retail prices of pork (loin) in 36 major and medium-sized cities, pork (hind leg) in 36 major and medium-sized cities, and pork in rural markets, the average value of these three variables was taken as a representative indicator of the “pork retail price” and compared with other variables under the “price” indicator. During this comparison, it was found that all variables were closely related to the pork retail price. Specifically, the price of two-way hybrid sows reflects breeding costs, indirectly affecting the profit margins and breeding intentions of farmers, thereby influencing pork prices and supply[4]. The ex-farm price of live hogs directly affects the market supply and demand relationship, and its increase may drive up the retail price of pork. The price of pork carcasses directly mirrors the retail price of pork in the market and is closely related to the final price paid by consumers. As for the national piglet price, although it fluctuates significantly, its impact on the retail price of pork does not show the same significant amplitude under the regulation of other factors affecting pork retail prices, but the trend is consistent.

For the variable under the “cost” indicator, the pig-grain price ratio is an important indicator for measuring the cost of pork production and market returns. It reflects the ratio of grain prices to live hog prices within the same period. Theoretically, when the pig-grain price ratio reaches or exceeds 6:1, farmers can break even or even make a profit; conversely, a ratio below 6:1 implies a risk of loss. When the pig-grain price ratio falls below this threshold, the National Development and Reform Commission will activate a three-tier early warning mechanism to monitor market risks and take corresponding measures. The trend chart of the pig-grain price ratio and net profit per live hog from March 2021 to February 2024 is shown in Figure 2.

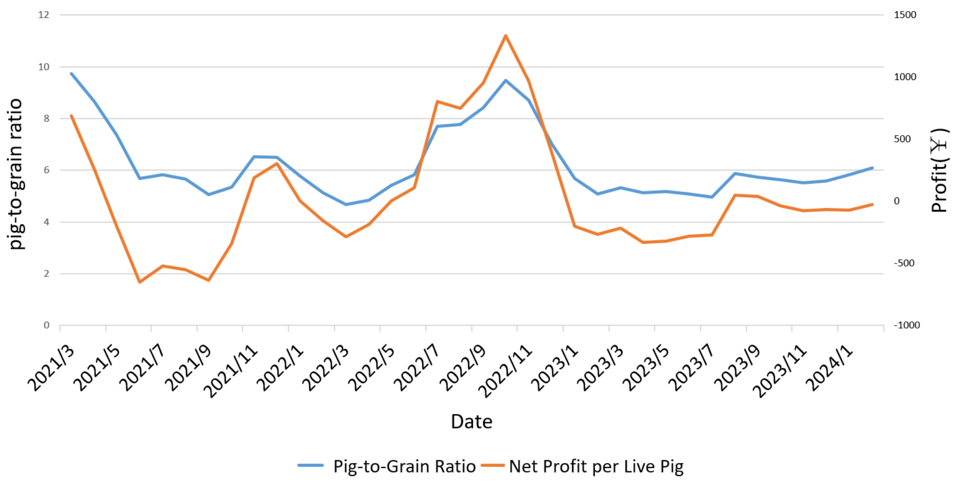

Figure 2.Trend Chart of Pig-Grain Ratio and Net Profit per Live Hog from March 2021 to February 2024

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As shown in the figure, from March 2021 to February 2024, the pig-grain ratio repeatedly fell into the third-level alert status, reflecting frequent operational losses that are consistent with the profit and loss situation per live hog. This highly volatile hog cycle has severely impacted the economic conditions of hog farmers. Despite the continuous decline in pork prices during periods of low pig-grain ratios, this is mainly due to factors such as oversupply of pork, reduced consumer demand, and relatively high grain prices. In such a market environment, the low pig-grain ratio further erodes the profits of hog farmers, forcing some to exit the market. From a long-term perspective, this could lead to a reduction in market supply and a potential rebound in pork prices.

3. Theoretical Foundation of the Hidden Markov Model

The HMM is a statistical model primarily used for the analysis of time-series data. Retaining the memoryless property of Markov processes, HMMs only need to consider the current state and transition probabilities when processing data, without requiring the entire history of the sequence. In an HMM, there are observable and hidden states, represented by the state sets Q and V, respectively.

$$\boldsymbol{Q} = \{\boldsymbol{q_1}, \boldsymbol{q_2}, \boldsymbol{q_3}, \ldots, \boldsymbol{q_N}\} \tag{2}$$

$$\boldsymbol{V} = \{\boldsymbol{v_1}, \boldsymbol{v_2}, \boldsymbol{v_3}, \ldots, \boldsymbol{v_M}\} \tag{3}$$

For each time point t, the state sequence I and the observation sequence O are composed of a hidden state $i_t$and an observation state o_t respectively.

$$\boldsymbol{I} = \{\boldsymbol{i_1}, \boldsymbol{i_2}, \boldsymbol{i_3}, \ldots, \boldsymbol{i_T}\} \tag{4}$$

$$\boldsymbol{O} = \{\boldsymbol{o_1}, \boldsymbol{o_2}, \boldsymbol{o_3}, \ldots, \boldsymbol{o_T}\} \tag{5}$$

Here, $\forall i_t \in Q, \forall o_t \in V$.

A Hidden Markov Model is composed of the state transition probability matrix, the observation probability matrix, and the initial state probability vector, which are denoted by A, B, and Π, respectively. Thus, the parameters of a model can be represented as

$$\boldsymbol{\lambda} = (\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\Pi}) \tag{6}$$

Given the observation sequence O, the model parameters λ are estimated through the Baum-Welch variant of the EM algorithm to maximize the probability of the observation sequence $P(O|\lambda)$ This process continues until the three parameters of the model converge or the maximum number of iterations is reached.

4. Empirical Analysis and Discussion of the Hidden Markov Model

4.1 Implementation of the Hidden Markov Model Algorithm

For futures price forecasting[5], the observations are the daily returns and closing prices of the futures. The hidden states are assumed to be three profit margins: “windfall profit,” “reasonable profit,” and “thin profit.” The HMM is constructed based on historical futures data and is further used to predict the closing prices of the futures.

This paper selects daily returns (ret), closing prices, and moving averages (ma_S) as features. Data from the past 30 days are used as the test set, while the remaining data from the training set is used to maintain the continuity of the time series.

In the HMM used in this paper, three parameters are first set: the number of hidden states, the method for calculating covariance, and the number of iterations. The number of hidden states is set to 3. The covariance calculation method is set to “diag” which means that the covariance matrix for each feature is assumed to be diagonal, i.e., there is no covariance between features. The number of iterations is set to 1000, which determines the convergence condition of the algorithm. The “fit” function is then called to train the model. This method uses the EM algorithm to determine the model parameters, including the state transition probabilities, emission probabilities (i.e., observation probabilities), and initial state probabilities. The trained mean matrix is shown in Eq. 7.

$$\begin{bmatrix} -0.1107 & 15390.7609 & 15410.2428 \\ -0.1439 & 20754.6971 & 20817.4106 \\ -0.0675 & 36951.9816 & 26990.7082 \end{bmatrix} \tag{7}$$

Each row represents a hidden state, and the three elements in each row correspond to the mean return rate, the mean closing price, and the mean trading volume, respectively. According to the results, the means under all three states are negative, indicating that the futures generally show a "downward" trend. The state transition matrix is shown in Eq. 8.

$$\begin{bmatrix} 0.9741 & 0 & 0.0259 \\ 0 & 0.9909 & 0.0091 \\ 0.0170 & 0.0029 & 0.9800 \end{bmatrix} \tag{8}$$

The observation that the values on the diagonal are relatively large indicates that states 0, 1, and 2 all tend to remain in their current states, implying that these states are relatively stable. The classification of hidden states is shown in Figure 3.

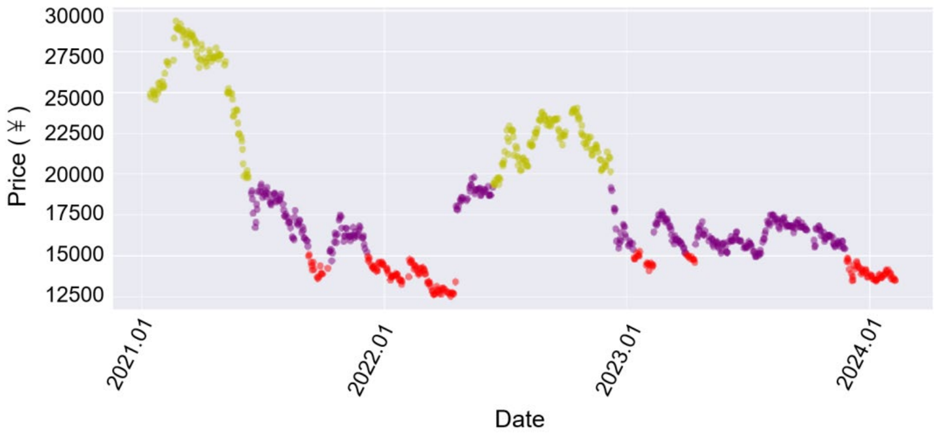

Figure 3. Classification Results of Hidden States

4.2 Results Analysis

In the process of model implementation, this paper intentionally introduced some random noise into the data to prevent overfitting. At the same time, the addition of random noise also enabled the model to learn more general patterns, thereby improving its performance on unknown data. The analysis shows that the futures price maintaining the supply-demand balance in the live hog market is between 17 and 23.75 yuan, corresponding to a pig-grain ratio between 5.82 and 7.77. According to the model's hidden state diagram, red and yellow represent periods of intense market fluctuation or high-risk states, while purple indicates relatively high profits in the live hog market during specific periods, covering several months in the second half of 2021, certain months in 2022, and multiple months in 2023.

The frequent occurrence of purple states is usually closely related to factors such as seasonal increases in market demand, supply chain fluctuations, policy adjustments, and international market dynamics. For example, the second half of 2021 often coincides with China's autumn consumption peak season, during which pork consumption significantly increases. In addition, as the market gradually adapted to the impact of African swine fever, pork supply began to recover, but the recovery speed of live hog inventory varied, which may have led to short-term mismatches in market supply and demand, thereby driving up prices. May and June of 2022 were the transition periods before the start of summer, which is usually an active period for live hog marketing and sales. At this time, market demand began to increase[6]. December, close to winter and the eve of the Spring Festival, saw a rise in stocking-up demand, and the low temperatures in winter may have affected the growth rate of pigs, slowing down the supply. Between 2021 and 2022, China's live hog futures prices were mainly affected by the COVID-19 pandemic, with lower demand. Therefore, only a few special periods during this time were relatively profitable for live hogs. After January 8, 2023, when China implemented "Category B management" measures for COVID-19, the live hog futures prices experienced a slight increase and maintained a stable fluctuation on this basis. As a result, there was a period of stable and relatively high profits in the live hog market in 2023. Moreover, the long duration in 2023 covered several important consumption seasons and may have been

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affected by changes in international trade policies and the pace of global economic recovery. These factors collectively influenced pork export demand and domestic prices. This comprehensive impact led to increased profits in the live hog market during these purple-marked periods, thereby helping market participants seize market opportunities.

5. Conclusions

This study employs the Hidden Markov Model (HMM) to analyze the live hog futures market using macroeconomic data from 2021 to 2024. By defining hidden states as "windfall profit," "normal profit," and "thin profit," the study identify the supply-demand equilibrium price interval at 17-21.75 yuan, with a corresponding pig-grain ratio of 5.82-7.77. The results highlight that substantial profit periods are closely linked to seasonal demand changes, supply chain fluctuations, policy adjustments, and international market dynamics. Notably, key profit-increasing periods include the autumn consumption peak in 2021, the pre-summer transition in 2022, and the market recovery following COVID-19 policy adjustments in 2023. Our research not only enriches the theoretical framework for predicting live hog futures prices but also provides a practical tool for market participants to estimate price intervals. By introducing the HMM, the study overcome the limitations of traditional point prediction methods, offering a more comprehensive reflection of the market's dynamic characteristics. The distinct state transition features of price fluctuations and pig-grain ratios under different states provide valuable references for decision-making.

Despite limitations in data timeliness and methodological innovation, this study demonstrates the feasibility of using HMM for live hog futures market analysis. Future research could explore the impact of additional macroeconomic factors to enhance the model's predictive accuracy and broaden its application scope.

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