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ORIGINAL ARTICLE

Is China's new live hog futures market efficient? Evidence from an analysis of market quality, price discovery and hedging effectiveness

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Abstract
On 8 January 2021, China's first live-animal and live-delivery futures product—in live hogs—was listed on the Dalian Commodity Exchange to serve as a risk management tool. We examine whether this newly established market exhibits good market quality and has realised its primary functions of price discovery and hedging. Our results suggest that the live hog futures market performs its price discovery function well and can hedge between 4% and 27% of the risk in the spot market, even though it is less actively traded, less liquid and more volatile than egg futures markets. To strengthen the hedging function of the live hog futures market, more effort—such as recruiting market makers and introducing night trading sessions—should be exerted to increase and smooth trading and stabilise volatility.

KEYWORDS
Chinese live hog futures market, hedging effectiveness, market quality, price discovery

JEL CLASSIFICATION
G11, G14, Q13

1 | INTRODUCTION

China is the largest pork producer and consumer in the world. In 2022, the year-end inventory of Chinese hogs was 453 million head (National Bureau of Statistics, 2022). Moreover, as an important staple food, pork accounts for around 54% of China's entire meat industry output and more than 60% of all meat consumed in China (Statista, 2022). However, the hog price in China has been highly volatile, especially after the outbreak of African swine fever (ASF) in August 2018. In November 2019, the hog price reached a historic high of 51 CNY (the equivalent of 7.41 USD) per kilogram—more than double the pre-ASF level—then fluctuated at this high level. Since 2021, hog prices have gradually decreased to 21 CNY (the equivalent of 3.05 USD) per kilogram, with a significant recovery of hog inventory. This roller coaster fluctuation poses great challenges to the Chinese hog industry.

The Chinese hog industry has sought to develop an effective risk management tool. In this context, the Chinese Securities Regulatory Commission (CSRC) allowed the Dalian Commodity Exchange (DCE) to launch live hog futures trading on 27 April 2020. By leveraging futures markets' primary functions of price discovery and hedging, hog producers can plan their production according to futures prices and capitalise on the futures market to hedge against spot price risks. On 8 January 2021, live hog futures debuted as China's first live-animal and live-delivery futures product. The listing of live hog futures has aroused great interest among investors. In the first listing year, the total trading volume and value of live hog futures were up to 6 million contracts and 1.7 trillion CNY, respectively (Sina, 2021). More than 2600 companies participated in futures trading and delivery, more than 90 companies have applied for permission to hedge, 19 of the top 20 leading pig breeding companies have applied to host the delivery warehouse and 11 companies have been allowed to do so (CFA, 2022). As an increasingly important risk management tool, it is crucial that we investigate the role and function of the Chinese live hog futures market.

Chinese live hog futures have been listed since January 2021, yet no research has examined the efficiency of this new market. This paper aims to study whether the market functions well; specifically, we focus on market quality, price discovery and hedging efficiency. Price discovery and hedging are the two primary functions of futures markets, and the improved performance of these functions relies on good market quality. For comparison, we also conduct these analyses on the previously established egg futures market for the first 2 years after its listing. We chose egg futures because eggs are one of the three fresh futures in China, along with hog futures and apple futures. Apple futures are not included because the data for apple spot prices are poor. We first measure three aspects of market quality: market activity, liquidity and volatility, following Fan et al. (2020). The price discovery function is measured as the relative contribution to the price discovery process compared with the spot market using the two mainstream models: information share (IS) (Hasbrouck, 1995) and component share (CS) (Booth et al., 1999; Chu et al., 1999; Harris et al., 2002). Since previous studies have proved that both the IS and CS models are sensitive to the relative level of noise in each market under review (Fassas, 2021), we employ two additional price discovery measures: the information leadership share (ILS) proposed by Putniņš (2013) and the information leadership indicator (ILI) proposed by Patel et al. (2020). Lastly, hedging efficiency is measured as hedging effectiveness based on the dynamic conditional correlation (DCC) model of Engle (2002), asymmetric DCC (ADCC) model of Cappiello et al. (2006) and generalised orthogonal (GO)-generalised autoregressive conditional heteroskedasticity (GARCH) model of Weide (2002). The rolling window method is used to calculate the out-of-sample optimal hedge ratios. A better hedging function is associated with greater hedging effectiveness, expressed as the degree of risk reduction that can be attained by applying the optimal hedge ratio.

Our results show that the new live hog futures market performs the price discovery function and can hedge risks in the live hog spot market, though its market quality is not as promising as that of egg futures. Using four price discovery contribution approaches, we find that the live hog futures market, rather than the spot market, dominates the price discovery process, but it is the opposite for eggs. The live hog futures market contributes more than 85% to the price discovery process, according to all price discovery contribution measurements. In contrast, the contribution of the egg futures market to the price discovery process is more than 85% based on the IS and CS models but less than 20% according to the ILS approach. We also test the hedging efficiency of live hog and egg futures based on the DCC-, ADCC-, and GO-GARCH models. Our results show that the live hog futures market can reduce 4%–27% of the spot market's risk. The hedging effectiveness of live hog futures is more than 25% using the

DCC- and GO-GARCH models but only 4% using the ADCC-GARCH model. In contrast, the hedging effectiveness of egg futures is less than 7% using all three GARCH models. Thus, we find that China's new live hog futures market performs generally well its primary functions of price discovery and hedging, though the market quality is not as good as that of egg futures.

We contribute to the literature in two ways. We are the first, to the best of our knowledge, to investigate the functional efficiency of the Chinese live hog futures market compared with the egg futures market. As the most valuable agricultural product in China, the listing of Chinese live hog futures has raised great interest—and also a concern—among pork industry stakeholders. Thus, verifying whether the live hog futures market performs its primary functions is essential. Second, we assess the market quality, price discovery and hedging effectiveness of the live hog futures market. We find that the price discovery and hedging function of Chinese live hog futures are good, though the market quality needs to be improved. The exchange should intensify efforts to popularise the new futures contract and consider introducing night trading sessions and market makers to attract more investors.

The remainder of the paper proceeds as follows. We review the related literature in Section 2, introduce the methodology in Section 3 and describe the data in Section 4. Empirical results and policy implications follow in Sections 5 and 6, and Section 7 concludes.

2 | LITERATURE REVIEW

The functional efficiency of commodity futures markets has been examined in a variety of studies. One strand of the literature focusses on market quality from the perspective of microstructure of financial markets. Due to data limitations, earlier studies tend to use spread estimators based on price changes following Thompson and Waller (1988) and Wang et al. (1997) or transaction prices following Hasbrouck (2004) as proxies for liquidity (Bryant & Haigh, 2004; Frank & Garcia, 2011; Martinez et al., 2011; Shah et al., 2012). In recent years, a growing number of studies on market quality of agricultural futures markets using a best-bid-offer (BBO) data set have emerged. For example, Wang et al. (2014) examine the relationship among trading volume, liquidity and volatility in the Chicago Mercantile Exchange (CME) corn futures market. Similarly, Costa et al. (2018) were the first to study the market quality of the Brazilian corn and live cattle futures markets. In the context of agricultural futures markets in China specifically, Liu et al. (2020) assess the market quality of Chinese commodity futures markets from the perspectives of liquidity, efficiency and volatility. Xu and Li (2018) investigate the liquidity of 15 Chinese commodity futures markets under different volatility levels, but they use daily or 5-min trading data instead of BBO data.

The second strand of literature concentrates on the price discovery function of commodity futures markets. Evidence from well-developed futures in the United States or Europe (Adammer et al., 2016; Consuegra & Garcia-Verdugo, 2017; Figuerola-Ferretti & Gonzalo, 2010; Jian et al., 2001; Kuiper et al., 2002) generally supports the theoretical conclusion that futures markets react more quickly to new information than do spot markets, due to greater liquidity, more transparency and lower transaction costs (Black, 1976; Brockman & Tse, 1995). In recent years, the price discovery process in Chinese agricultural commodity markets has drawn the interest of scholars. For example, He and Xie (2012) find that the Chinese sugar spot market has more pricing power than the futures market, while Yan and Reed (2014) and Demir et al. (2019) provide evidence on corn and cotton futures markets' dominant roles in the price discovery process. Yan and Zhao (2019) demonstrate that the cornstarch futures market in China is efficient for price discovery, although it is a newly emerged market. Li and Xiong (2021) find that for 11 of 14 commodities, futures markets dominate the price discovery process.

A third strand focusses on the hedging efficiency of futures markets. The hedging effectiveness measure proposed by Ederington (1979) is a major criterion for evaluating the efficiency of different hedging instruments. The basic idea of a hedging strategy is to take opposite positions in spot and futures markets for the same underlying asset (Ederington, 1979). The optimal hedge ratio (the share of the futures position used to cover a spot position) can be obtained by estimating the slope term of an ordinary least square (OLS) regression in which the spot return is regressed on the futures return. However, the hedge ratio estimated by OLS does not account for variation in the spot and futures prices over time. The multivariate GARCH method developed by Bollerslev et al. (1988) accounts for the conditional variance and covariance of spot and futures prices and is thus increasingly used to estimate hedge ratios (Chang et al., 2011; Li et al., 2021; Wang et al., 2015; Yang & Allen, 2005).

Empirical studies have examined the functional efficiency of Chinese agricultural futures markets (Demir et al., 2019; Ju & Yang, 2019; Li & Xiong, 2021; Liu et al., 2020). However, these studies focus on only one or two aspects of market quality, price discovery and hedging effectiveness. Moreover, research on the efficiency of the live hog futures is scarce, which motivates us to comprehensively study the efficiency of the Chinese live hog futures market.

3 | METHODOLOGY

3.1 | Market quality measurement

We measure three aspects of market quality: market activity, liquidity and volatility. Following Ryu (2013), indexes for market activity include the total daily volume, the total daily number of trades and trade size (large, medium and small). We define large trades as more than 50 contracts per trade, medium trades as 5–50 contracts per trade and small trades as fewer than five contracts per trade on each trading day. Because live hogs have high contract value, given the same trading value, the trading volume for live hog futures could be much smaller than egg futures. Therefore, we also include trading value as a market quality index and compare the trading values of live hog and egg futures.

We also measure market quality from the perspective of liquidity. Following Xu et al. (2020), we use market depth, which reflects the order flow needed to move a price by a certain amount, and we also use two spread measures—the quoted spread (QS) and the effective spread (ES)—that reflect trading costs. Market depth is the average of the bid size and ask size. We calculate QS as the difference between the ask price and the bid price, divided by the mid-quote prevailing for each trade. We calculate ES as $\mathrm{ES}_{i,s} = \frac{2\times q_{i,s}\times |p_{i,s}-m_{i,s}|}{m_{i,s}}$; where $q_{i,s}$ is the trade indicator of the sth trade calculated using the algorithm developed by Lee and Ready (1991); $p_{i,s}$ denotes the transaction price; and $m_{i,s}$ is the midpoint between the bid and ask price. The daily depth and ES are time-weighted averages, while the daily ES is a volume-weighted average.

To measure volatility, we calculate short-term volatility, defined as the highest quote midpoint in an interval minus the lowest quote midpoint in the same interval, divided by the midpoint between the high and low values (Xu et al., 2020).

3.2 | Price discovery measures

We first measure price discovery by calculating the contribution of the futures market to the price discovery process relative to the spot market using the IS and CS models. Both the IS and CS methods are based on the binary vector error correction model (VECM), as follows:

$$\Delta P_t = \alpha\beta P_{t-1} + \sum_{i=1}^{I} \Gamma_i \Delta P_{t-i} + \varepsilon_t \tag{1}$$

where $P_t = \left(P_{1,t}, P_{2,t}\right)'$ is a vector of the prices of futures and spot prices at time t. According to Hasbrouck (1995), Equation (2) can be written as:

$$P_t = \Psi(1)\sum_{j=1}^{t}\varepsilon_j + \Psi^*(L)\varepsilon_t \tag{2}$$

where $\Psi(1) = \Psi\sum_{k=0}^{\infty}\Psi_k$.

The IS model defines the price discovery performance of one market as the portion of the efficient equilibrium price variance that can be attributed to this market. Then, the price discovery contribution of market i is calculated as

$$\mathrm{IS}_i = \frac{\left(|\Psi M|_i\right)^2}{\Psi\Omega\Psi}, i = 1, 2, \tag{3}$$

where $MM' = \Omega$; Ω is the variance–covariance matrix from Equation (2) and M is the Cholesky factorisation of the matrix Ω. The IS model is affected by the order of the price series in the Cholesky factorisation. Thus, we compute the upper and lower bounds of IS for each potential ordering and take the average, as in Baillie et al. (2002). The sum of the two markets' IS values equals 1. Thus, if the information share of one market exceeds 0.5, that market dominates the price discovery process.

The CS model is based on the permanent–transitory model proposed by Gonzalo and Granger (1995). In this method, the price can be divided into permanent and transitory components, such that the permanent component is $f = \gamma\prime P_t$, where $\gamma = \left(\alpha\prime_\perp\beta_\perp\right)^{-1}\alpha\prime_\perp$ and $\alpha\prime_\perp\alpha = 0$ and $\beta\prime_\perp\beta = 0$. According to Harris et al. (2002), γ can be used to calculate the relative contribution of market i to price discovery:

$$\mathrm{CS}_i = \frac{\left(\alpha_{\perp,i}\right)^2}{\alpha_{\perp,i} + \beta_{\perp,i}}, \quad i = 1, 2 \tag{3}$$

Similarly, $\mathrm{CS}_1 + \mathrm{CS}_2 = 1$; when the CS value of one market is higher than 0.5, that market plays a dominant role in the price discovery process.

However, when the level of noise between two markets differs, the IS and CS models may lead to overstating the price discovery contribution of the market with lower levels of noise (Hu et al., 2020; Yan & Zivot, 2010). Consequently, Putniņš (2013) proposed the ILS measure to address the confounding effects of noise on the IS and CS methods. The ILS approach is robust to differences in noise in two price series. To calculate ILS, the information leadership (IL) is first calculated as:

$$\mathrm{IL}_1 = \left|\frac{\mathrm{IS}_1}{\mathrm{IS}_2}\frac{\mathrm{CS}_2}{\mathrm{CS}_1}\right|, \mathrm{IL}_2 = \left|\frac{\mathrm{IS}_2}{\mathrm{IS}_1}\frac{\mathrm{CS}_1}{\mathrm{CS}_2}\right| \tag{4}$$

where IL_1 and IL_2 are the IL measures for futures and spot markets, respectively. Then, the ILS is defined as:

$$\mathrm{ILS}_1 = \left|\frac{\mathrm{IL}_1}{\mathrm{IL}_1 + \mathrm{IL}_2}\right|, \mathrm{ILS}_2 = \left|\frac{\mathrm{IL}_2}{\mathrm{IL}_1 + \mathrm{IL}_2}\right| \tag{5}$$

Similar to the IS and CS measures, a value of ILS above 0.5 indicates a stronger contribution to price discovery.

Lastly, we also adopt the ILI method proposed by Patel et al. (2020) to measure price discovery. Unlike other price discovery measures, the ILI is a binary measure that equals one if ILS is above 0.5 and zero otherwise. According to Patel et al. (2020), the ILI is calculated from ILS:

$$\mathrm{ILI}_i = \begin{cases} 1 & \text{if } \mathrm{ILS}_i > 0.5 \\ 0 & \text{if } \mathrm{ILS}_i < 0.5 \end{cases} \tag{6}$$

3.3 | Hedging efficiency measures

We use the DCC-, ADCC- and GO-GARCH models to capture the dynamic conditional correlations and hedge ratios between futures and spot markets. For brevity, we only present the GO-GARCH model as an example. For more details on the DCC and ADCC models, please refer to Pham (2019). Under the GO-GARCH model, the return r_t is a function of the conditional mean m_t and an error term ε_t. The GO-GARCH model maps the residual ε_t onto a set of unobservable independent factors f_t. Then, the error term becomes the function of $\varepsilon_t = Af_t$ where the mixing matrix A can be decomposed into an unconditional covariance matrix $\sum$ and a rotation matrix U. Therefore, the matrix can be written as $A = \sum^{1/2} U$. In matrix A, the rows are the assets and the columns are the factor (f_t). The factor is specified as $f_t = H_t^{1/2} Z_t$, where Z_t is a stochastic variable with mean zero and variance 1. Given the well-defined A and f_t, the conditional equation becomes $r_t = m_t + AH_t^{1/2} Z_t$. The conditional covariance matrix of the returns is $\sum_t = AH_tA'$. The rotation matrix and its dynamics can be jointly estimated by independent component analysis (ICA) (Zhang & Chan, 2009).

Based on the GARCH models, we obtain the optimal hedge ratios and hedging effectiveness. The return of the portfolio consisting of futures and spot transactions is written as $r_{p,t} = r_{S,t} - h_t^* r_{F,t}$, where $r_{F,t}$ and $r_{S,t}$ are the returns of the futures and spot markets on day t, respectively; h_t^* denotes the optimal hedge ratios on day t. The optimal hedge ratios are calculated as $h_t^* = \frac{\mathrm{cov}_{\mathrm{SF},t}}{\mathrm{var}_{F,t}}$, where $\mathrm{cov}_{\mathrm{SF},t}$ is the conditional covariance between spot and futures returns and $\mathrm{var}_{F,t}$ is the conditional variance of the futures returns. The optimal hedge ratios imply that the long position of futures should be hedged by a short position of the spot market to minimise portfolio risk. The hedging efficiency of the futures market is measured by the hedging effectiveness index (Chang et al., 2011) as $\mathrm{HE}_t = \frac{\mathrm{var}_{S,t} - \mathrm{var}_{p,t}}{\mathrm{var}_{S,t}}$, where $\mathrm{var}_{S,t}$ represents the risk of the spot market and $\mathrm{var}_{p,t}$ represents the risk of the hedged portfolio. The higher the HE, the more efficient the futures market as a hedging tool.

Out-of-sample hedge ratios are constructed using the rolling window method. At each time point, a one-period-ahead conditional volatility forecast is calculated and then used to calculate the one-period-ahead optimal hedge ratio. Forecasted optimal hedge ratios are used to construct the hedged portfolio. A rolling window size of $N - 100$ observations is applied to calculate 100 one-period-ahead hedge ratios, where N denotes the sample size for live hog and egg futures.

4 | DATA

We use two sets of data to measure the market quality, price discovery and hedging efficiency of the live hog futures market. Specifically, we use tick-by-tick data to calculate three types of market quality indexes—market activity, liquidity and volatility; price discovery and hedging functions are measured using daily futures and spot prices. Our sample spans the period 8 January 2021 (the launch date) to 8 January 2023—that is, the 2-year period after Chinese live hog futures' listing. For comparison, we obtain data on egg futures from 8 November 2013 to 6 November 2015—that is, the first 2 years after its listing. First, we obtain tick-by-tick data on live hog and egg futures from *Tick Data* (www.tickdata.com) to calculate market quality indexes. The tick-by-tick data provide quotes on the best bid and best ask prices, with timestamps to the nearest millisecond. For each quote, the corresponding number of contracts available to trade is also specified. We focus on the daytime session, from 9:00 to 11:30 and 13:00 to 15:00, since live hog futures do not have night trading sessions. For live hog futures, six contracts that expire in January, March, May, July, September and November are traded simultaneously on each trading day. To generate continuous series, we use contracts with the highest trading volume in the current month following Yang et al. (2020).

In addition, to investigate the price discovery and hedging functions, the daily live hog spot price is collected from the Bric database (http://www.agdata.cn/). We obtain national average live hog and egg prices for spot markets and derive the daily settlement price of live hog and egg futures from the tick-by-tick data. To match spot and futures price series, we only collect observations that have both futures and spot prices on a given day. Futures markets in China are closed on weekends and holidays, and on those days, there is no price for futures. To address this, we match spot prices with futures prices for each commodity by deleting observations for spot prices on the days when the futures markets are closed. In this way, we obtain 471 and 427 observations for the live hog and egg markets, respectively. Figure 1 displays the daily futures and spot prices of live hogs from 8 January 2021 to 8 January 2023 and eggs from 8 November 2013 to 8 November 2015. For live hogs, both futures and spot prices are highly volatile and exhibit a similar trend for most of the sample period; for eggs, the spot price is apparently more volatile than the futures price, and the two prices show a large divergence from March to June 2015. Summary statistics for the returns are shown in Table 1. For both live hog and eggs, futures returns have greater amount of variability than spot returns. The JB test shows that each series is far from normally distributed. Unit root tests indicate that each series of daily returns is stationary.

5 | EMPIRICAL RESULTS

In this section, we first assess and compare three aspects of the market quality of live hog and egg futures: market activity, liquidity and volatility. Then, we employ IS, CS, ILS and ILI models to quantify the price discovery contribution of the futures market relative to the spot market for live hogs and eggs. Lastly, we investigate the hedging effectiveness of live hog and egg futures markets against the risk of the corresponding live hog and egg spot prices.

5.1 | Market quality

We first calculate market quality indexes using tick data on live hog and egg futures. Figure 2 displays the live hog futures market quality measurements compared with those of the egg futures market. As shown in Figure 2, live hog futures exhibit worse market activity, liquidity and price volatility. Specifically, live hog futures have lower trading volume, fewer trades and smaller proportions of large and medium trades but do attract a considerable volume of small trades. The average trading volume is 20,922 contracts for live hog futures and 169,004 for egg futures—and thus the average number of egg futures trades is considerably higher than that of live hog futures. However, the differences in trading values of live hog and egg futures are much smaller; moreover, the median trading value for live hog futures is even slightly higher than that for egg futures. With regard to trade size, live hog futures attract an average of over 85% small trades but have only 0.1% large trades. For egg futures, small trades also account for a large proportion, with an average of over 50%. However, the proportions of medium and large trades are considerably higher for egg futures than for live hog futures. Compared with the egg futures markets, live hog futures are less actively traded. This might be because one

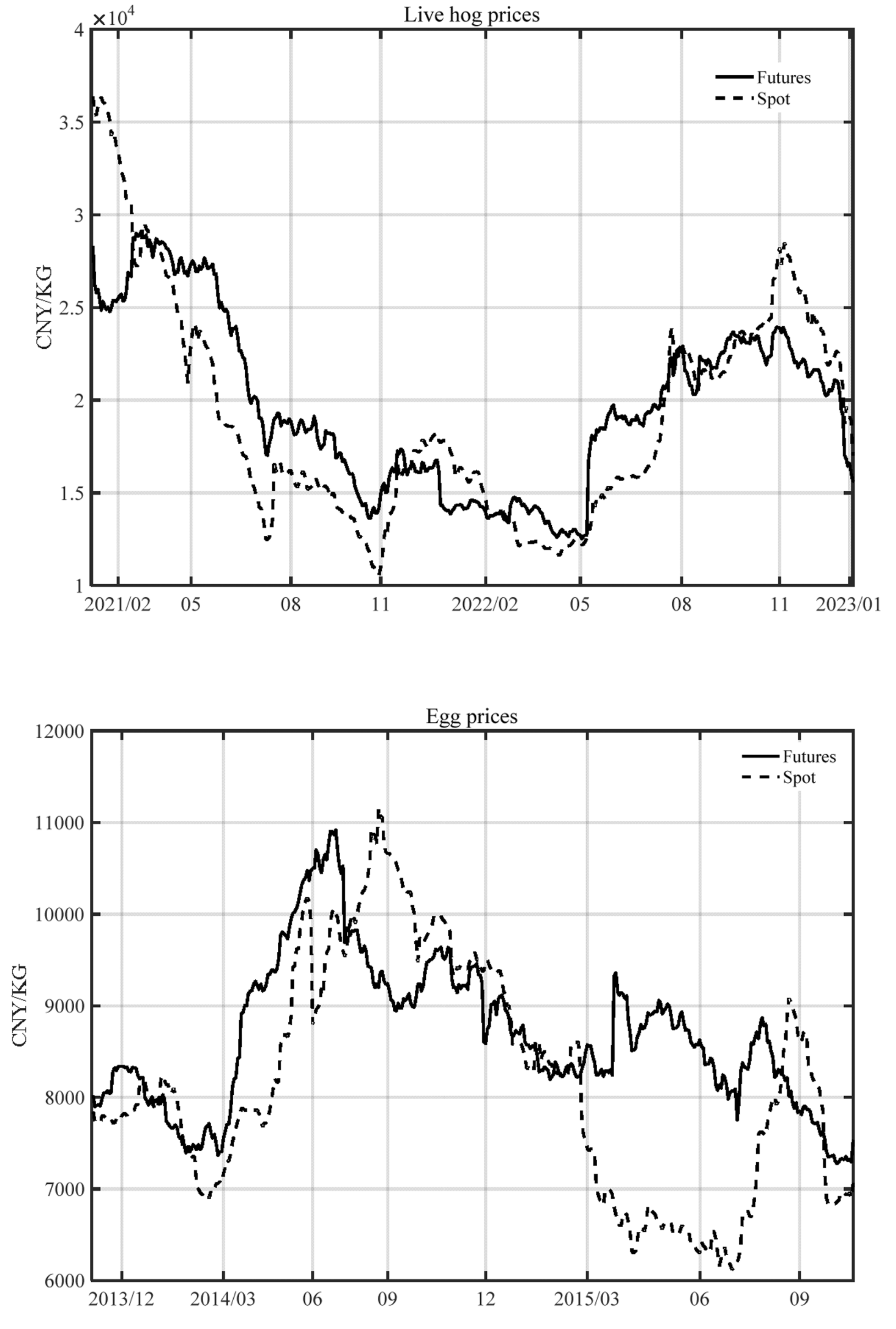

FIGURE 1 Live hog and egg futures and spot prices during the first 2 years after listing. *Note*: Solid lines denote futures prices and dashed lines denote spot prices for live hog and egg.

TABLE 1 Summary statistics for futures and spot returns for live hog and egg.

	Live hog		Egg	
	Futures	Spot	Futures	Spot
Mean	−0.125	−0.186	−0.015	−0.025
Median	−0.163	−0.162	0.024	0.000
Maximum	27.212	21.219	12.338	5.964
Minimum	−11.999	−10.173	−8.277	−12.182
SD.	2.311	2.542	1.306	1.529
Skewness	3.091	1.800	1.144	−1.632
Kurtosis	46.812	18.149	27.307	17.250
Jarque-Bera	38,337.880***	4748.272***	10,580.050***	3793.345***
ADF	−17.767***	−16.165***	−19.138***	−14.759***

Note: For each data series, continuously compounded daily returns are calculated as $100 \times \ln\left(\frac{p_t}{p_{t-1}} - 1\right)$ where p_t is the daily futures or spot price. ADF denotes the Augmented Dickey–Fuller test to verify whether daily returns are stationary.

***Significance at 0.01.

contract for live hog futures is much more expensive than for egg futures. Specifically, one contract for live hog futures is equal to 16 tonnes of live hogs, whereas one contract for egg futures is equal to 5 tonnes of eggs. Taking the first listing day as an example, the settlement price of live hog futures was 28,290 CNY/MT on 8 January 2021. At that time, the value of one live hog futures contract was 452,649 CNY. For egg futures, the settlement price was 8020 CNY/MT on 8 November 2013. The value of one egg futures contract was 40,100 CNY—less than one-tenth of one live hog futures contract. The smaller difference between trading values of live hog and egg futures is also a sign of live hog futures' high contract value.

Moreover, swine breeding is dominated by small farmers in China. In 2021, the number of pig farms that produce fewer than 49 heads per year, between 50 and 99 heads per year and between 100 and 499 heads per year account for 93.5%, 3.5% and 2.1% of total hog farms, respectively. In contrast, the number of pig farms that produce more than 50,000 heads per year accounts for less than 0.01% in the same year (MARA, 2022). The lack of large-scale producers' participation could also lead to the small trade size.

The depth of the live hog futures market is also smaller, meaning that it takes less order flow to move the price of live hog futures. The average market depth of live hog futures is 7, while it is 50 for egg futures. In contrast, the live hog futures market has larger QS and ES for liquidity. Market participants face higher trading costs when trading live hog futures than egg futures, and investors have to pay a high price to complete a trade. The live hog futures market is less liquid than the egg futures market. In addition, the live hog futures market also has significantly larger short-term volatility. Thus, the live hog futures market is more volatile than the egg futures market. Overall, the live hog futures market has poorer quality compared with the egg futures market.

5.2 | Price discovery

Next, we measure the price discovery function of live hog and egg futures using the IS and CS models. Table 2 displays the results from the price discovery contribution of futures and spot markets for live hogs and eggs. As Table 2 shows, the live hog futures market contributes 94.2% to the price discovery process based on the IS model and 97.7% based on the CS model. Similarly, the price discovery contribution of the egg futures market is 93.9% according to

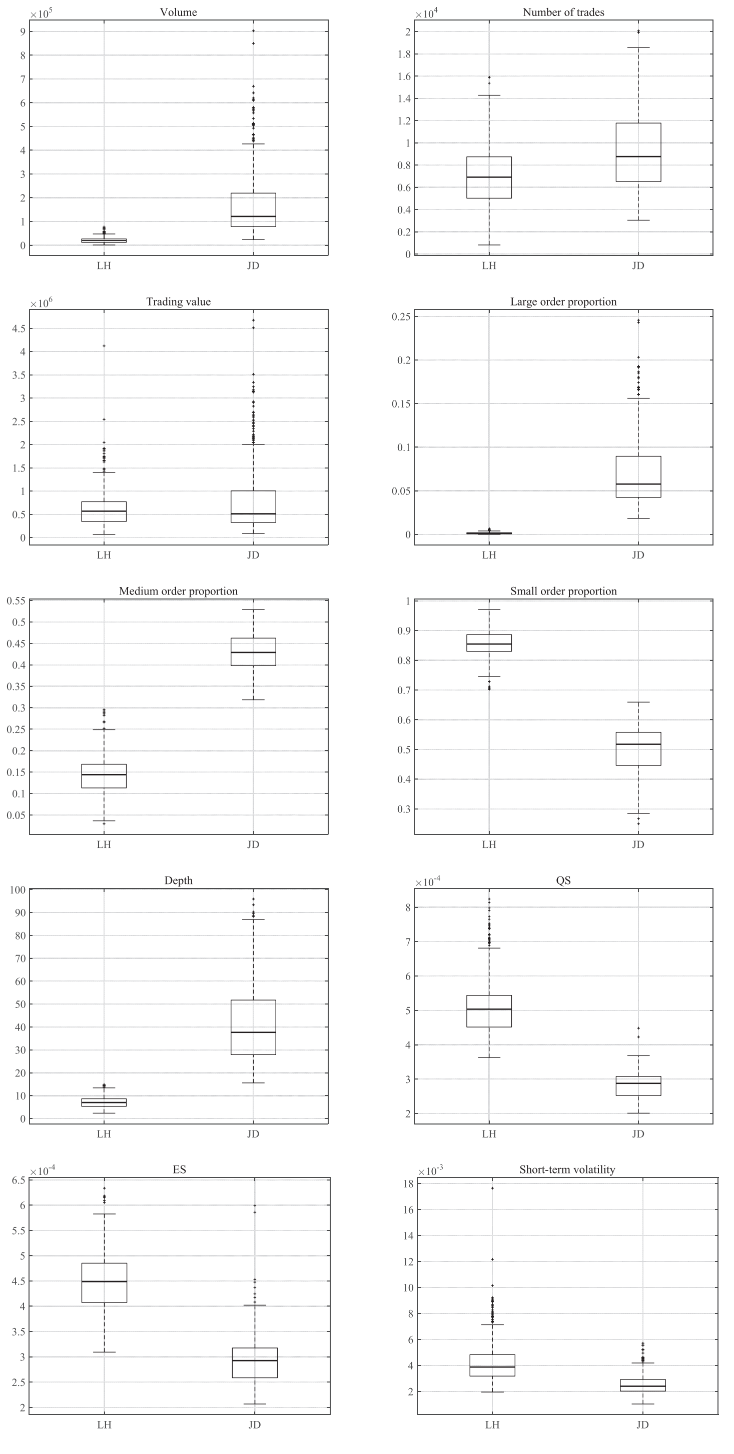

FIGURE 2 Market quality of live hog and egg futures during the first 2 years after listing. *Note*: LH and JD are the ticker symbols of Chinese live hog and egg futures, respectively. Thus, the two boxes denote the distribution of market quality for live hog and egg futures in each figure. The bottom edge, horizontal line in the middle and top edge of each box represent the 25th percentile, median and 75th percentile of the distribution of market quality, respectively. Whiskers extending beyond the box indicate minimum and maximum market quality values. Each + symbol denotes an outlier.

TABLE 2 Price discovery contribution from the IS and CS models.

Commodity	Market	IS	CS	ILS	ILI
Live hog	Futures	0.942	0.977	0.872	1
		(0.884, 0.999)			
	Spot	0.058	0.023	0.128	0
		(0.001, 0.116)			
Egg	Futures	0.939	0.859	0.135	0
		(0.908, 0.970)			
	Spot	0.061	0.141	0.865	1
		(0.030, 0.092)			

Note: IS and CS denote price discovery contribution calculated by the information share model and component share model, respectively. Values in paratheses denote the upper and lower bounds of price discovery contribution calculated by the IS model, respectively. The IS for each market is calculated as the mean of the upper and lower bounds. ILS and ILI denote the information leadership share and information leadership indicator, respectively.

the IS model and 85.9% according to the CS model. The IS and CS models commonly suggest that for the market for live hogs and eggs, new information is first incorporated in the futures market; thus, the futures market rather than the spot market dominates the price discovery process.

However, the results differ using the ILS and ILI methods, especially for eggs. Consistent with previous studies, the IS and CS models are likely to overstate the price discovery contribution (Hu et al., 2020; Yan & Zivot, 2010). Specifically, for live hogs, the futures market still dominates the price discovery process based on the ILS and ILI models; however, the contribution of the live hog futures market calculated from the ILS model is slightly lower than results from the IS and CS models. In contrast, for egg futures, the price discovery contribution falls below 0.5 using the ILS model, and thus, the ILI is 0. This suggests that the egg spot market rather than the futures market dominates the price discovery process.

Overall, all four price discovery contribution measurements suggest that for the market for live hogs, new information is first incorporated into the futures market; as a result, the futures market rather than the spot market dominates the price discovery process. Thus, the price discovery performance of the live hog futures market is good. For eggs, in contrast, the ILS and ILI methods suggest that the price discovery function of futures markets is not good, and the IS and CS methods overstate the price discovery contribution of futures markets. The poor price discovery performance of the egg futures market could be explained by the large divergence of the egg futures price from the spot price. As shown in Figure 1, live hog futures and spot prices share a similar trend, but the egg futures price diverges from the spot price to a large degree, which could hinder the price discovery function.

5.3 | Hedging effectiveness

The third part of our empirical results involves the hedging efficiency of the live hog futures market based on the DCC-, ADCC- and GO-GARCH models. We start by estimating several versions of the DCC model. Each specification includes a constant in the mean equation and GARCH (1,1) variance equation but differs regarding whether an AR(1) term is included in the mean equation and the choice of distribution. We find that the DCC with an AR(1) term in the mean equation estimated with a multivariate *t* distribution fits best for the live hog futures market, while the DCC with an AR(1) term in the mean equation estimated with a multivariate normal distribution fits best for egg futures. The models are selected based on minimisation of the Akaike information criterion (AIC). Therefore, all three GARCH models are estimated with an AR(1) term in the mean equation for live hogs and eggs. The DCC and ADCC models are estimated with a multivariate t distribution for live hogs and a multivariate normal distribution for eggs. The GO-GARCH model is estimated with a multivariate affine negative inverse Gaussian distribution.

Tables 3 and 4 present the estimation results of the DCC- and ADCC-GARCH models. Estimated coefficients on the AR(1) term (a) in the mean equation are positive and statistically significant at the 1% level for both the live hog spot and egg spot markets. The parameters α are positive and statistically significant for the live hog spot market, which provides evidence for short-term persistence in the live hog spot price. Parameters β are positive and statistically significant for live hog futures and spot prices and egg futures, which provides evidence for long-term persistence. Estimated asymmetric terms (γ) are significantly negative for egg futures, which indicates that positive residuals increase the variance (conditional volatility) more than negative shocks of the same magnitude do. Estimated coefficients θ_1 and θ_2 are positive and sum to less than unity. Thus, the dynamic conditional correlations are mean-reverting. The shape parameter λ is equal to the degrees of freedom in the t distribution. As λ approaches infinity, the shape of the t distribution approaches the normal distribution.

TABLE 3 Estimation results from the DCC-GARCH model.

	Live hog market				Egg market			
	Coef.	**SE**	***t***	**Prob**	**Coef.**	**SE**	***t***	**Prob**
Spot								
μ	−0.250	0.091	−2.737	0.006	0.130	0.107	1.216	0.224
a	0.398	0.049	8.110	0.000	0.276	0.140	1.972	0.049
ω	1.163	0.522	2.228	0.026	1.179	0.366	3.223	0.001
α	0.576	0.157	3.675	0.000	0.814	0.591	1.377	0.168
β	0.423	0.171	2.474	0.013	0.000	0.072	0.000	1.000
λ	2.727	0.265	10.275	0.000				
Futures								
μ	−0.145	0.079	−1.842	0.065	−0.012	0.065	−0.189	0.850
a	−0.010	0.045	−0.230	0.818	0.070	0.043	1.645	0.100
ω	0.159	0.080	1.990	0.047	0.007	0.012	0.638	0.524
α	0.000	0.007	0.000	1.000	0.000	0.006	0.000	1.000
β	0.983	0.002	543.505	0.000	0.996	0.001	1693.576	0.000
λ	2.525	0.347	7.273	0.000				
DCC coefficients								
θ_1	0.000	0.000	0.000	1.000	0.000	0.000	0.001	0.999
θ_2	0.901	0.261	3.458	0.001	0.896	0.051	17.608	0.000
λ	4.000	0.397	10.073	0.000				
Information criteria								
AIC	8.252				6.854			
BIC	8.394				6.978			
Shibata	8.25				6.852			
H-Q	8.308				6.903			
LL	−1923				−1447			

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; H-Q, Hannan–Quinn criterion; LL, likelihood.

TABLE 4 Estimation results from the ADCC-GARCH model.

	Live hog market				Egg market			
	Coef.	SE	t	Prob	Coef.	SE	t	Prob
Spot								
μ	−0.254	0.093	−2.733	0.006	−0.024	0.087	−0.275	0.783
a	0.398	0.049	8.080	0.000	0.274	0.067	4.070	0.000
ω	1.131	0.543	2.081	0.037	0.052	0.030	1.699	0.089
α	0.528	0.197	2.683	0.007	0.071	0.042	1.676	0.094
β	0.427	0.175	2.440	0.015	0.952	0.033	28.688	0.000
γ	0.089	0.249	0.356	0.722	−0.079	0.038	−2.115	0.034
λ	2.739	0.312	8.776	0.000				
Futures								
μ	−0.145	0.079	−1.835	0.067	−0.009	0.057	−0.166	0.868
a	−0.004	0.052	−0.071	0.944	0.044	0.055	0.795	0.427
ω	0.460	0.442	1.040	0.298	0.049	0.018	2.687	0.007
α	0.007	0.014	0.517	0.605	0.000	0.001	0.000	1.000
β	0.881	0.110	8.019	0.000	0.983	0.000	55,415.079	0.000
γ	0.136	0.099	1.376	0.169	−0.023	0.012	−1.938	0.053
λ	2.825	0.734	3.848	0.000				
DCC coefficients								
θ_1	0.000	0.003	0.000	1.000	0.243	0.091	2.658	0.008
θ_2	0.956	0.030	31.918	0.000	0.000	0.115	0.000	1.000
θ_3	0.018	0.029	0.609	0.542	0.000	0.305	0.000	1.000
λ	4.000	0.927	4.313	0.000				
Information criteria								
AIC	8.17				6.864			
BIC	8.337				7.016			
Shibata	8.166				6.861			
H-Q	8.236				6.924			
LL	−1900				−1446			

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion, H-Q, Hannan–Quinn criterion; LL, likelihood.

Table 5 presents the results of the GO-GARCH model. Panels A, B and C of Table 5 show the rotation matrix (U), the mixing matrix (A) and the parameter estimates, respectively. The GO-GARCH model estimates the factors and thus does not provide any standard errors. The long-run persistence (β) is considerably larger than the short-run persistence (α) for both live hogs and eggs. The sum of short-term and long-term persistence (α and β) is less than one, which indicates that the volatility process is mean-reverting.

Next, we employ the rolling window method to calculate out-of-sample hedge ratios. Figure 3 displays one-step-ahead forecasts of optimal hedge ratios. For both commodities, ADCC hedge ratios have the largest variability—but the hedge ratios of live hogs are considerably larger than those for eggs, according to all three GARCH models. Table 6 presents summary statistics of out-of-sample hedge ratios and hedging effectiveness. The average of the hedge ratios between live hog futures and spot prices is 0.608 for the DCC model, which

TABLE 5 Estimation results from the GO-GARCH model.

	Live hog		**Egg**	
Panel A: The rotation matrix U				
	U(1)	U(2)	U(1)	U(2)
U(1)	0.684	0.73	−0.379	−0.925
U(2)	0.73	−0.684	−0.925	0.379
Panel B: The mixing matrix A				
	A(1)	A(2)	A(1)	A(2)
A(1)	0.252	2.527	0.124	1.522
A(2)	2.505	0.419	1.301	0.088
Panel C: GO-GARCH parameter estimation				
	Spot	Futures	Spot	Futures
ω	0.004	0.161	0.542	0.037
α	0	0.579	0.021	0.039
β	0.995	0.42	0.352	0.943
Skew	0.039	0.038	−0.06	0.086
Shape	0.428	0.36	0.316	0.107
LL	−1956		−1258	

Note: For GO-GARCH, the multivariate *t* distribution is not an option and is estimated with a multivariate affine negative inverse Gaussian (MANIG) distribution.

Abbreviation: LL, likelihood.

indicates that one long position in the live hog spot market can be hedged by a short position of 0.608 in the live hog futures market. By comparison, the average of hedge ratios between live hog futures and spot is 0.836 for the ADCC model and 0.661 for the GO-GARCH model. The DCC model provides the highest hedging effectiveness and the ADCC model is the least effective. Based on the DCC model, hedging in the live hog futures market can lead to 27.933% risk reduction compared with an unhedged spot position, but only 4.352% risk reduction using the ADCC model.

For eggs, the mean of optimal hedge ratios ranges from 0.151 to 0.243, which indicates that one long position in the egg spot market can be hedged by a short position of 0.151 to 0.243 in the egg futures market. Specifically, average optimal hedge ratios are 0.151, 0.162 and 0.243 for the DCC-, ADCC- and GO-GARCH models, respectively. The mean of optimal hedge ratios is the largest using the GO-GARCH model, and hedging effectiveness is the highest using the DCC model. Based on the DCC-GARCH model, hedging in the egg futures market can lead to 6.311% risk reduction compared with an unhedged spot position. Hedging is shown to be least effective using the ADCC-GARCH model, which can reduce risk by 1.137% in the spot market.

Overall, using DCC-, ADCC- and GO-GARCH models, the live hog futures market can reduce between 4.352% and 27.933% of risk in the live hog spot market, while egg futures can reduce between 1.137% and 6.311% of risk in the egg spot market. The hedging effectiveness of Chinese live hog futures is considerably larger than that of egg futures, which suggests that live hog futures can hedge more risk in the spot market and are thus more efficient in the hedging function. The results for hedging effectiveness are consistent with the results for price discovery measurements—that is, the price discovery function of the live hog futures market is promising, which leads to a higher degree of risk reduction in the spot market. In contrast, the price discovery function of egg futures is not promising and thus is unlikely to reduce much risk in the spot market.

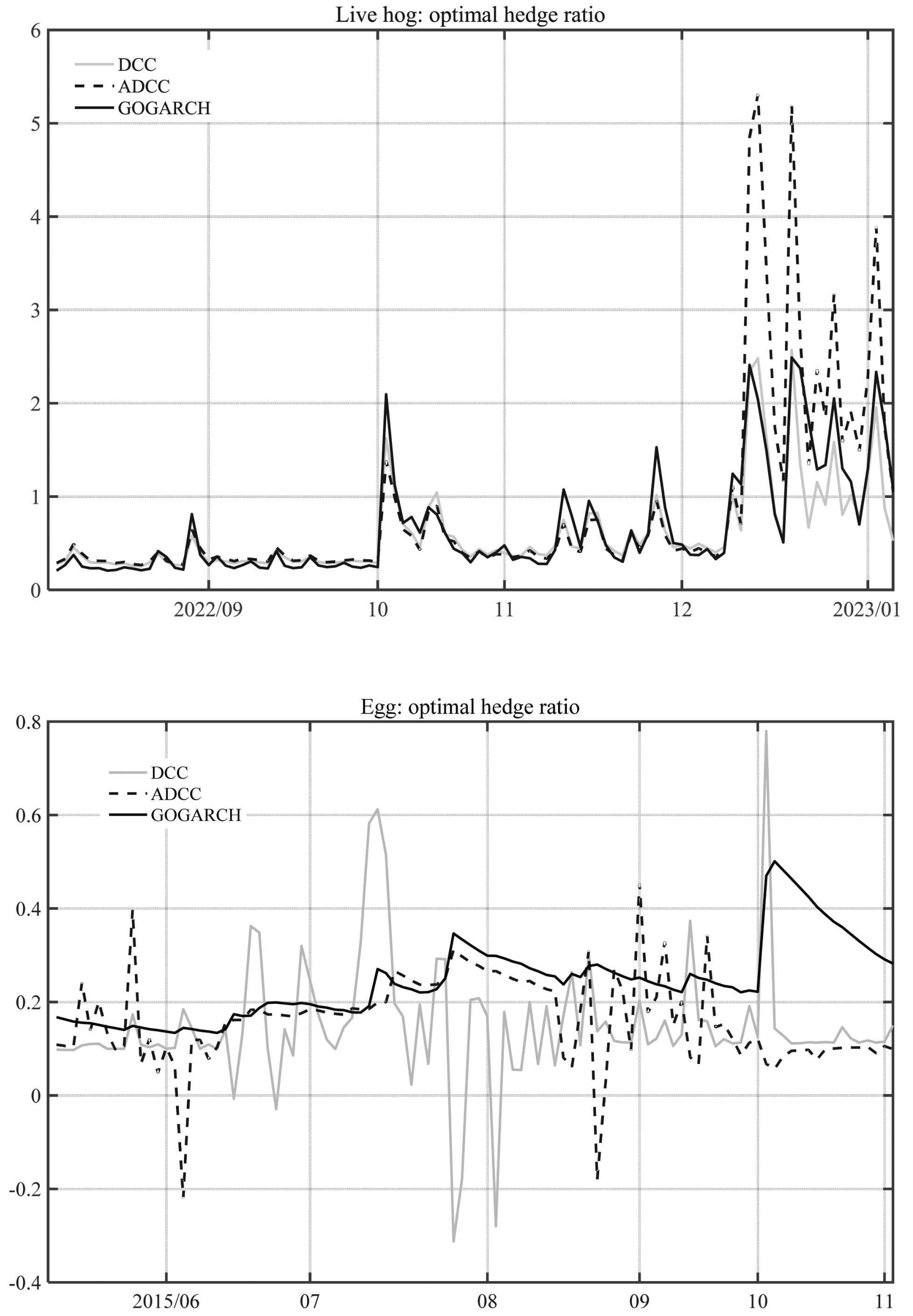

FIGURE 3 Rolling one-step-ahead optimal hedge ratios. *Note*: The grey solid line, black dashed line and black solid line denote optimal hedging ratios calculated using DCC-, ADCC- and GO-GARCH models, respectively.

To conclude, the price discovery and hedging performance of live hog futures are good despite less active trading, lower liquidity and higher volatility. The live hog futures market contributes over 85% to the price discovery process. Meanwhile, live hog futures can hedge

TABLE 6 Hedge ratio summary statistics and hedging effectiveness.

	Mean	Max	Min	SD	HE (%)
Live hog market					
DCC	0.608	2.573	0.252	0.473	27.933
ADCC	0.836	5.312	0.266	1.033	4.352
GO-GARCH	0.661	2.490	0.207	0.581	25.653
Egg market					
DCC	0.151	0.780	−0.313	0.140	6.311
ADCC	0.162	0.453	−0.220	0.096	1.137
GO-GARCH	0.243	0.501	0.134	0.085	4.839

Note: Hedge ratios are calculated from fixed-width rolling analysis, which produces 100 one-step-ahead forecasts. HE measures the hedging effectiveness of a portfolio constructed under the optimal hedge ratio strategy compared with an unhedged long position in the live hog spot market.

27% of risk in the spot market. Though good compared with the egg futures market, there is still room for improvement in the live hog futures market's hedging effectiveness. Previous studies have proved that active trading, high liquidity and price stability are associated with the high price efficiency of the futures market and can thus enhance hedging performance (Lee et al., 2009). Given that the live hog market is less active, less liquid and more volatile, improvement in market quality is an excellent choice for improving the hedging efficiency of the live hog futures market.

6 | POLICY IMPLICATIONS

China's hog industry suffers from the "hog cycle" phenomenon, and risk in the hog industry expanded with the outbreaks of ASF in China. Many hog firms suffered from losses, and many small-scale hog farms were squeezed out. For example, Muyuan Foodstuff—China's second-largest pig producer—reported a net loss of 155.7 million yuan for the first half of 2019 (Reuters, 2019) and the number of hog farmers who produce fewer than 49 heads per year, between 50 and 99 heads per year and between 100 and 499 heads per year decreased by 28%, 25% and 23%, respectively, in 2019 compared with 2018 (MARA, 2019, 2020).

The live hog futures can help market participants make more informed production decisions, such as expansion or reduction in production capacity for hogs. Our results suggest that live hog futures realised the primary functions of price discovery and hedging effectiveness, though market quality is not good. The live hog futures market functioned well in the first 2 years after listing, which could provide long-awaited opportunities for participants in China's hog industry to manage risk.

Large-scale hog firms can benefit from hedging using these new live hog futures. Listing of the new live hog futures has attracted interest from live hog companies. For instance, in 2021, 13 companies announced their participation in live hog futures hedging, including leading companies such as Muyuan Foodstuff and New Hope Group. In 2022, the number of hog firms that participated in hedging using live hog futures increased to 16 (Futures Daily, 2023). The participation of large-scale hog firms in hedging, in turn, is likely to enhance the market quality of live hog futures.

Small-scale farms can use Insurance Plus Futures, a new agricultural cooperation mode in China, to participate in the live hog futures market indirectly. The plan complements the futures market and provides a valuable opportunity for small-scale hog farmers who may not have sufficient knowledge or capital to directly participate in live hog futures trading. At the same time, the effectiveness of the program relies on the efficient functioning of the live hog futures market. Our results show that the live hog futures market functions well, which suggests that small-scale farms can use Insurance Plus Futures to transfer risk. As stated previously, hog production in China is dominated by small-scale farms. Along with the listing of live hog futures, the live hog Insurance Plus Futures project was initiated to provide government subsidies to insurance companies that offer agricultural income insurance policies based on fluctuating futures prices. Specifically, hog farms buy live hog price insurance from insurance companies, which transfer farms' risk to the insurance companies. At the same time, insurance companies buy over-the-counter options from futures companies for reinsurance. Then, futures companies trade live hog futures and can thus transfer the risk to the live hog futures market. In 2021, there were 125 Insurance Plus Futures projects for live hogs, which covered 0.25 million tonnes (2.22 million head) of live hogs (Securities Daily, 2023).

Market quality could be further improved, though the price discovery and hedging functions are good. Compared with egg futures in the first 2 years after listing, the live hog futures market exhibits less trading activity, lower liquidity and higher volatility. Recruiting market makers would be a good option to improve market quality. In May 2022, the DCE started to recruit market makers for live hog futures, and in June of the same year, the DCE announced 10 futures and securities companies that would be qualified market makers for live hog futures (DCE, 2022). Also, live hog futures do not have night trading. In future, the DCE could consider introducing a night trading session to enable live hog futures to better connect with international markets.

7 | CONCLUSION

China is the largest pork producer and consumer in the world. However, the hog price is highly volatile, especially after the outbreak of ASF in 2018. In 2021, the DCE launched live hog futures to stabilise the market and boost industrial-scale development. In this paper, we examine the quality, price discovery and hedging function of this market compared with the previously established egg futures market. Our findings suggest that the market quality of live hog futures requires improvement given its less active trading, lower liquidity and larger volatility compared with the egg futures markets. Despite the poor market quality, the live hog futures market performs well with respect to the price discovery function, as does the egg futures market. Also, using three GARCH models, we see that the live hog futures market can hedge between 4% and 27% of risk in the spot market, whereas egg futures can hedge less than 7% of risk in the spot market. Though good compared with egg futures, there is still room for improvement in the live hog futures market's hedging effectiveness. In future, the market quality of live hog futures should be improved to enhance the risk management function.

Establishing the live hog futures market in China is essential, given the highly volatile live hog spot market. Our findings shed light on the market condition of China's newly established live hog futures. To improve the market quality and hedging efficiency of the live hog futures market, more market participants in the live hog industry are expected to be involved in hedging using live hog futures. Large-scale hog firms can hedge these live hog futures directly, while medium- and small-scale hog companies and farmers can choose Insurance Plus Futures as a risk management tool. Recruiting market makers and opening night trading are good options for enhancing the market quality of live hog futures.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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