https://doi.org/10.17221/278/2023-AGRICECON

Are futures markets functioning well for agricultural perishables? Evidence from China's apple futures market

Qianqian Mao[1,2,3], Jens-Peter Loy[3], Thomas Glauben[4], Yanjun Ren[5,4]*

[1]School of Economics, Zhejiang University of Technology, Hanghzou, China
[2]Institute for Industrial System Modernization, Zhejiang University of Technology, Hangzhou, China
[3]Department of Agricultural Economics, University of Kiel, Kiel, Germany
[4]Leibniz Institute of Agricultural Development in Transition Economies (IAMO), Halle, Germany
[5]College of Economics and Management, Northwest A & F University, Yangling, China

*Corresponding author: yanjun.ren@nwafu.edu.cn

Citation: Mao Q.Q., Loy J.P., Glauben T., Ren Y.J. (2023): Are futures markets functioning well for agricultural perishables? Evidence from China's apple futures market. Agric. Econ. – Czech, 69: 471–484.

Abstract: Emerging economies often establish commodity futures markets to discover price signals, manage price risks and improve market integration, but establishing a futures market may not be feasible for agricultural perishables. In this study, we evaluated the function of the world's first fresh fruit futures contract for apples. Combining partial cointegration with state-space modelling, we derived time-varying price discovery metrics for the apple futures market. Our findings revealed a limited and time-varying dominance of price discovery by the futures market, while a substantial share of price discovery occurred in the spot market. Moreover, poor convergence of disaggregated spot prices to the futures price suggests that commercial traders in the apple supply chain tended to focus more on the spot market than on the futures market. Thus, emerging economies should be cautious about the new establishment of futures markets for agricultural perishables. Future research using more specific data on the spot market may provide a better insight on the limited function of the futures market.

Keywords: market integration; partial cointegration; price discovery; price transmission

Agricultural commodity markets have been subject to frequent price shocks over the past few decades (Etienne et al. 2015). These shocks have brought great challenges to emerging economies, which are the major buyers and sellers of agricultural commodities. To discover price signals, manage price risks and improve market integration, emerging economies (primarily acting as price takers for agricultural commodities) are inclined to establish domestic futures markets (Mohanty and Mishra 2020; Perera et al. 2020; Yang et al. 2021). However, not all agricultural commodities are capable of being used for futures trading (Brorsen and Fofana 2001; Singh 2012; Hu et al. 2020). The perishability of agricultural commodities has often been considered to affect the function of futures markets (Yang et al. 2001; Sanders and Manfredo 2002; Ankamah-Yeboah et al. 2017). A well-functioning futures market is more likely to be found for storable grains,

Supported by Zhejiang Educational Department, China under grant No. Y202248790, the Research Funds for Zhejiang University of Technology, China under grant No. SKY-ZX-20220258 and GB202301003, the Qinchuangyuan Project of Shaanxi Province, China under grant No. QCYRCXM-2022-145, and the National Natural Science Foundation of China under grant No. 72373117.

https://doi.org/10.17221/278/2023-AGRICECON

such as corn and soya beans, whereas the markets of perishable commodities tend to be fragmented and local, mainly because of their relatively high storage and delivery costs (Fan and Wei 2006). Nevertheless, many agricultural perishables have been introduced into futures trading, which brings a lasting academic and public concern to the function of these new futures markets (Hu et al. 2020). Some argue that the futures markets function well and provide efficient price signals (Bohl and Stephan 2013; Bohl and Sulewski 2019; Bohl et al. 2020), whereas others think that the price signals are distorted because the corresponding spot markets are fragmented and too many speculators enter the futures markets (Huchet and Fam 2016).

Thus, in this study, we aimed to investigate whether futures markets function effectively for agricultural perishables, and if not, what may have caused their failure. Could failure be attributed to the tremendous speculation introduced by futures markets or some other features of commodity spot markets? We selected the fresh apple futures market as our research focus, mainly because of its perishable nature and its large share of fresh fruit markets worldwide (ZCE 2018). At the end of 2017, the trade of fresh (Red Fuji) apple futures contracts started at the Zhengzhou Commodity Exchange (ZCE) in China. This futures market is the first for fresh fruits worldwide. It became very popular among traders, and ranks 12th among the top 20 agricultural futures contracts by trade volume (*TV*) worldwide (FIA 2021). On May 15, 2018, the turnover of the apple futures contracts reached EUR 33.5 billion, which surpassed even the turnover of the Shanghai Stock Exchange in China. This extremely large *TV* raised public concerns about overheated speculation. A comprehensive investigation of this new futures market could have important implications for other agricultural perishables.

To measure the function of futures markets, investigators in previous studies mostly tested the existence of a long-run cointegration relationship (Working 1948; Brenner and Kroner 1995; Pindyck 2001) and then derived time-invariant price discovery indicators (Baillie et al. 2002; Rittler 2012; Dimpfl et al. 2017). We extended this line of study in two ways.

First, we combined the partial cointegration test with state-space modelling (Adämmer and Bohl 2018; Vollmer et al. 2020) and generated time-varying price discovery indicators for the apple futures market. Compared with the Markov switching vector error correction models (VECMs), which allow for only a limited number of regimes, this model can generate a time-varying estimation of parameters at each time point. A dynamic indicator of the price discovery function would be more useful for regulators to monitor the operation of futures markets and enable exploration of the relationship between the speculation level and the futures market function more precisely.

Second, investigators in previous studies often ignored the information contained in the disaggregated price series of regional spot markets. On the basis of the law of one price, a well-functioning futures market can promote the price convergence level of different regional spot markets. We tested whether the price convergence level changed before and after the introduction of the apple futures market.

Following the procedure just outlined, we found a limited and time-varying dominance of price discovery by the apple futures market, while a substantial share of price discovery occurred in the spot market. Poor convergence of disaggregated spot prices to the futures price suggests that commercial traders in the apple supply chain tended to focus more on the spot market than on the futures market. Moreover, we found no evidence supporting the argument that a high speculation level results in the limited function of the futures market.

MATERIAL AND METHODS

The apple market in China

Being the largest producer, consumer and exporter of apples, China produced 56% of the global apple output (45.97 million tons) in 2021. The planting area of apples is approximately 2 million ha. The main apple species in China is the Red Fuji, which accounts for more than 70% of the total apple production. In 2016, 42.62 million tons of apples were consumed, which amounts to 30 kg per capita in China (ZCE 2018).

Apple trees bloom during May, and the apples are harvested during September in China. After the harvest, some of the apples are sold for immediate consumption, and the rest are stored in cooling warehouses for consumption over the year (before the next harvest). Both cold and frosty weather during pollination time and hailstones during the maturation period greatly affect the yields of apple trees. Thus, harvests of different marketing years vary substantially owing to weather conditions. For instance, the apples harvested in 2018 suffered from bad weather conditions, and the apples harvested in 2019 were much better in terms of quality and quantity.

Apple trees are one of the most important cash crops for rural households in China. However, historical

https://doi.org/10.17221/278/2023-AGRICECON

performance of the apple market indicates that both good and bad weather conditions can significantly affect apple prices. Although good weather conditions might bring a good harvest for farmers, the price would drop because of the massive supply. Farmers are unable to handle these price risks and may even fail to cover their costs. Other commercial traders in the apple supply chain, such as wholesalers, processors and exporters, are subject to the same risk. For example, in 2015, the apple price volatility peaked when it reached 150% per year. In this context, the apple futures market is designed as a financial tool for price discovery and risk sharing. Given that China is the largest producer, consumer and exporter of apples, the apple futures market might also provide important price signals for other apple markets worldwide.

There are seven delivery months for the apple futures contracts – namely, January, March, May, July, October, November and December. The product code is AP, and the trading unit of one apple futures contract is 10 metric tons per lot physically delivered. The daily price limit (fluctuation up and down) is 5%. The quality of apples should meet the Chinese national standard, GB/T 10651–2008, or the so-called first-class standard—fresh apples with fruit width greater than or equal to 80 mm, the fruit width tolerance not greater than 5% and quality tolerance not greater than 10% (ZCE 2018).

Data

We obtained the apple futures and spot (daily) price series from the ZCE website and WIND online data set, respectively (WIND 2022; ZCE 2022). For the futures price, we used the concatenated nearby futures contract prices from December 22, 2017, to December 31, 2021. We used the daily *TV* and open interest (*OI*) data from ZCE to construct an indicator of speculation level – namely, $\Delta OI/TV$, where Δ is the first difference operator (Lucia and Pardo 2010). The lower (higher) value of $\Delta OI/TV$ denotes a higher (lower) speculation level.

For the spot price, we used the Qianhai wholesale price index (*QWPI*) of Red Fuji apples (WIND 2022). China's Ministry of Commerce uses it as an official price indicator of apples. The *QWPI* refers to a *TV* weighted average wholesaling price index of Red Fuji apples from different markets in China. Because the futures price aggregates information from apple traders nationwide, we used this index to proxy the national average price of apples. The sample period was from January 1, 2016, to December 31, 2021, which enabled us to compare the performance of the apple spot market between the periods before the futures market (January 1, 2016–December 21, 2017) and after (December 22, 2017–December 31, 2021). The quality of apples that the *QWPI* refers to includes both the first-class standard and the second-class standard. This quality difference can be captured by a partial cointegration relationship. Finally, we use the individual price series contained in the *QWPI* to calculate the convergence level (WIND 2022). The data on these disaggregated price series were collected from 35 wholesale markets in China. We took the logarithm of all prices.

Methods

Our empirical analysis followed three steps as described here. We estimated the models in the R programming language (version 4.2.0) and Stata (version 16.0).

Unit root test with structural breaks and partial cointegration. The augmented Dickey-Fuller (ADF) test loses power if structural breaks are present in time series (Perron 1989). Figure 1 shows that the apple futures price had structural breaks. We thus used the flexible Fourier stationary test developed by Enders and Lee (2012). Without assuming that the dates, the precise number and the exact form of the breaks (either instantaneous or gradual structural change) are known a priori, the Fourier stationary test enabled us to test the stationarity of each price series in a more flexible way.

Afterward, we tested whether there was a partial cointegration relationship between the apple futures price p_t^f and the spot price p_t^s (Clegg and Krauss 2018):

$$p^f_t = \beta_1 p^s_t + W_t \tag{1}$$

$$W_t = M_t + R_t \tag{2}$$

$$M_t = \rho M_{t-1} + \varepsilon_{M,t} \text{ with } \varepsilon_{M,t} \sim N(0, \sigma^2_M) \tag{3}$$

$$R_t = R_{t-1} + \varepsilon_{R,t} \text{ with } \varepsilon_{R,t} \sim N(0, \sigma^2_{Mr}) \tag{4}$$

where the vector $[1, -\beta_1]$ represents the partial cointegration relationship, similar to standard cointegration. However, the residual part W_t contains a permanent part R_t and a transient part M_t. The permanent part R_t follows a random walk and denotes the time-varying basis between the apple futures and spot prices. It is subject to many factors, such as quality difference, different harvests and the concatenation of nearby futures contracts. The transient part M_t follows a stationary autoregressive process of order 1 (AR[1] process) with coefficient

https://doi.org/10.17221/278/2023-AGRICECON

Figure 1. Apple futures and spot prices

spot price – apple spot price; futures price – apple futures price
Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

ρ. The innovations $\varepsilon_{M,t}$ and $\varepsilon_{R,t}$ are assumed to be independent of each other and follow normally distributed white noise processes.

Compared with the other tests that can identify the cointegration relationship with a limited number of regime shifts, such as that of Gregory and Hansen (1996), the partial cointegration model estimates the long-run relationship between the apple futures and spot prices in a more flexible way. It decomposes the residual part W_t into the permanent part R_t and the transient part M_t. Both R_t and M_t are time-varying and allow the long-run relationship between the apple futures and spot prices to change every period. As outlined, the basis between the apple futures and spot prices can be subject to many factors, such as quality difference, different harvests and the rollover of nearby futures contracts. Thus, the partial cointegration test enabled us to capture the time-varying shifts in the long-run relationship between the apple futures and spot prices (Vollmer et al. 2020).

Clegg and Krauss (2018) developed a two-step likelihood ratio test procedure for this partial cointegration relationship. The first step was to test whether W_t follows a pure random walk (null hypothesis H_0^R: no cointegration). If the null hypothesis H_0^R is rejected, we find either a standard cointegration relationship (if W_t follows a pure AR(1) process) or a partial cointegration relationship (if W_t follows a partial AR(1) process). The second step tests whether W_t follows a pure AR(1) process (the null hypothesis H_0^M). If H_0^R and H_0^M are both rejected, there would be a partial cointegration relationship.

Time-varying partially cointegrated VECM. If p_t^f and p_t^s were partially cointegrated, we used the time-varying VECM model developed by Vollmer et al. (2020) to rewrite Equations (1) and (2) as follows:

$$\begin{bmatrix}\Delta p_t^f\\ \Delta p_t^s\end{bmatrix}=\begin{bmatrix}\alpha^f\\ \alpha^s\end{bmatrix}\left(\begin{bmatrix}1-\beta_1\end{bmatrix}\begin{bmatrix}p_{t-1}^f\\ p_{t-1}^s\end{bmatrix}-R_{t-1}\right)+ \\ +\sum_{i=1}^{k}B_i\begin{bmatrix}\Delta p_{t-i}^f\\ \Delta p_{t-i}^s\end{bmatrix}+\begin{bmatrix}v_t^f\\ v_t^s\end{bmatrix} \tag{5}$$

$$=\begin{bmatrix}\alpha^f\\ \alpha^s\end{bmatrix}M_{t-1}+\sum_{i=1}^{k}B_i\begin{bmatrix}\Delta p_{t-i}^f\\ \Delta p_{t-i}^s\end{bmatrix}+\begin{bmatrix}v_t^f\\ v_t^s\end{bmatrix} \tag{6}$$

where: Δ – first difference operator; the parameters α^f and α^s control how quickly the p_t^f and p_t^s adapt to deviations from their long-run equilibrium relationship; B_i – matrix of the short-run adjustment coefficients; residuals υ_t^f and υ_t^s – white noise processes. We used the Akaike information criterion to determine the lag order k. Given that $\left(\begin{bmatrix}1 & -\beta_1\end{bmatrix}\begin{bmatrix}p_{t-1}^f\\ p_{t-1}^s\end{bmatrix}-R_{t-1}\right)=M_{t-1}$, the error correction term of the model contains only the transient part M_{t-1}.

https://doi.org/10.17221/278/2023-AGRICECON

To obtain time-varying estimates of the parameters, we transformed Equation (5) into the state-space form:

Observation equation:

$$P_t = Z_t\xi_t + \varepsilon_t \text{ with } \varepsilon_t \sim N(0,\Theta_t) \tag{7A}$$

State equation:

$$\xi_t = I\xi_{t-1} + \upsilon_t \text{ with } \upsilon_t \sim N(0, \Phi_t) \tag{7B}$$

where: $P_t = \begin{bmatrix} \Delta p_t^f \\ \Delta p_t^s \end{bmatrix}$ – left-hand side vector of price changes in Equation (5); Z_t arrays the right-hand side variables of the VECM equations in block diagonal form; I – identity matrix of dimension $2 \times (2k + 1)$, which corresponds to the column dimension of Z_t and the row dimension of ξ_t; ε_t, υ_t – serially uncorrelated error terms with zero mean and covariance matrices Θ_t and Φ_t. Applying the Kalman filter produced optimal estimates of the state variables ξ_t at each time t (Vollmer et al. 2020).

We used the time-varying state variable ξ_t including the parameters α^f_t and α^s_t to calculate the dynamic indicator of price discovery function (Vollmer et al. 2020). Three methods well established in the literature are the permanent-transitory (*PT*) measure (Gonzalo and Granger 1995), the information share (*IS*) measure (Hasbrouck 1995) and the information leadership share (*ILS*) measure (Putniņš 2013). They gauge different dimensions of price discovery – namely, timeliness and efficiency. The dimension of timeliness describes how quickly the futures price reflects changes in the fundamental value of a commodity. The dimension of efficiency denotes how effectively a price avoids noise in its adjustment to the fundamental value. The *PT* measure refers to the dimension of efficiency, and the *ILS* measure reflects the dimension of timeliness; the *IS* measure reflects both (Yan and Zivot 2010). Higher values imply a more prominent contribution to price discovery.

For the time-varying *PT* measure:

$$PT_t^f = \frac{\alpha_t^s}{\alpha_t^s - \alpha_t^f},\ PT_t^s = 1 - PT_t^f \tag{8}$$

where: PT^f_t (PT^s_t) measures the contribution of the futures (spot) market in terms of efficiency.

For the time-varying *IS* measure:

$$IS_t^f = \frac{\left(\left[\Psi_t F_t\right]^f\right)^2}{\Psi_t \Omega_t \Psi_t},\ IS_t^s = 1 - IS_t^f \tag{9}$$

where: Ψ_t – long-run impact matrix of the vector moving average representation of the VECM form at time t; F_t – transformed version of the error covariance matrix Ω_t. The time-varying Ω_t is obtained through a BEKK–multivariate generalised autoregressive conditional heteroscedasticity method. Lien and Shrestha (2009) proposed using an eigen-decomposition of Ω_t to obtain a unique matrix F_t.

For the time-varying *ILS* measure:

$$ILS_t^f = \frac{IL_t^f}{IL_t^f + IL_t^s},\ ILS_t^s = 1 - ILS_t^f \tag{10}$$

where: $IL_t^f = \left|\frac{IS_t^f PT_t^s}{IS_t^s PT_t^f}\right|$ and $IL_t^s = \left|\frac{IS_t^s PT_t^f}{IS_t^f PT_t^s}\right|$.

Measurement of price convergence. On the basis of the law of one price, the prices of the same product sold in different markets would converge to the same level. Similarly, a well-functioning futures market is supposed to promote the price convergence level of different regional spot markets because an efficient futures market can involve different types of traders who reveal their private information on the market through bidding on the futures contracts. In a market in which no one has all the information on supply and demand conditions, auction theory implies that a trader would adjust his or her price expectation on the basis of others' quotes (Milgrom 2017). Thus, the divergence between an efficient futures price and each regional market's spot price may motivate local traders to access new information and adjust their price expectations accordingly, which may further increase the price convergence among different regional markets.

We measured the convergence level of disaggregated spot prices to different benchmarks – the mean value of regional spot prices and the futures price. Improving convergence to the mean value of regional spot prices or the futures price would indicate the formation of a unified national market for apples, and increasing convergence to the futures price would suggest a well-functioning futures market.

We constructed a new relative price series as $RP_{it} = \ln(P_{it}/\bar{P}_t)$, where P_{it} is the apple spot price of market i at time t and $\bar{P}_t$ is the mean spot price of different regional markets at time t. Moreover, we used the apple futures price to construct another relative price series, $RFP_{it} = \ln(P_{it}/FP_t)$, where FP_t is the futures price at time t.

https://doi.org/10.17221/278/2023-AGRICECON

Finally, we measured the convergence level of spot prices by testing the stationarity of each relative price (RP_{it} and RFP_{it}). Convergence to the law of one price means that the relative price (RP_{it} and RFP_{it}) is mean reverting or stationary (Fan and Wei 2006). Thus, we performed the ADF test on every relative price series and used the panel unit root test method – namely the MW test (Maddala and Wu 1999). Moreover, to account for the storage and delivery costs in different marketplaces, we use the partial cointegration test to check the stationarity of every relative price series, as well. The permanent part R_t in Equations (2) and (4) can capture the storage and delivery costs of each regional market because they tend to persist in the long run.

RESULTS AND DISCUSSION

Unit root test and partial cointegration analysis. The results of the unit root test with a nonlinear Fourier function and the ADF test in Table 1 show that the apple futures and spot prices are nonstationary, whereas their first difference terms are stationary (see the last two columns of Table 1).

Although the apple spot price (*QWPI*) has a common trend with the futures price in Figure 1, there is no tight connection between them over the sample period. After an initial period of price divergence, these two prices tended to have a common process. During July 2019, the futures and spot prices deviated from each other again. The futures price dropped on July 1, 2019, whereas the spot price continued to increase. This price divergence reflects that the apple futures contracts of July and October corresponded to different harvests or different marketing years, and the inventory of apples was running out during this period. The July contract corresponds to the apples harvested in 2018, and the October contract corresponds to the apples harvested in 2019. The reduction in the apple yields caused by bad weather in 2018 resulted in an inventory shortage during July 2019. Because of the low inventory of agricultural perishables, arbitrage could not work effectively to link the futures and spot prices together (Yang et al. 2001).

Table 1. Unit root test with a nonlinear Fourier function (H_0: price has a unit root)

Unit root test	*RSS*	*k*	$\tau_{LM}(k)$	*ADF*
Futures price	0.6487	1	–3.5900	–1.5730
QW index	0.6087	5	–1.2000	–1.9860
Futures price returns	0.6562	1	–29.5800***	–21.2100***
QW index returns	0.6562	1	–29.5800***	–11.7820***

***P < 0.01; *RSS* – residual sum of squares; $\tau_{LM}(k)$ – test statistics for the unit root test with a nonlinear Fourier function (Enders and Lee 2012); $k = 1$ or $k = 5$ is chosen based on the minimum of residual sum of squares; QW – Qianhai wholesale price index for Red Fuji apples

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

We then tested whether there was a partial cointegration relationship between the apple futures and spot prices. The results on the top panel of Table 2 show that the first null hypothesis (W_t follows a pure random walk) and the second null hypothesis (W_t follows a pure AR[1] process) were both rejected. Thus, the apple futures and spot prices were partially cointegrated with each other. More details on the estimation results are listed in the middle panel of Table 2.

The advantage of the partial cointegration relationship is that it can decompose the cointegration residuals W_t into the transient part M_t and the permanent part R_t. In Table 2, $R^2_{MR} = 0.4130$ means that only 41.30% of the total variance in the deviations from the long-run equilibrium relationship is explained by the transient part, M_t, whereas the rest (58.70%) is explained by the permanent part, R_t. This finding suggests a relatively large basis between the apple futures and spot prices.

As mentioned, many factors could affect the path of R_t. For example, Figure 1 shows that the concatenation of futures contracts generated structural breaks in the apple futures price; the same applies to the R_t process. In the bottom panel of Table 2, we compare the mean absolute value changes of R_t (namely, $|\Delta R_t| = |R_t - R_{t-1}| = |\varepsilon_{Rt}|$) between the time points of futures contract concatenation and other time points. On average, the values of $|\Delta R_t|$ were significantly higher when the apple futures contracts rolled over from the nearest contract to the next nearest one, which is consistent with the price breaks caused by contract rollover.

Another public concern regarding the apple futures market is whether its higher speculation level results in higher basis risk between the futures and spot prices (Van Huellen 2018). We compared the absolute mean deviation of R_t (namely, $|R_t - \bar{R}_t|$) with the speculation level (measured by ΔOI / TV). We plotted the value of $|R_t - \bar{R}_t|$ and ΔOI / TV together in Figure 2 and found no significant relationship between these two series. Comparisons among the mean values of $|R_t - \bar{R}_t|$ for different quantile intervals of ΔOI / TV showed that

https://doi.org/10.17221/278/2023-AGRICECON

Table 2. Partial cointegration relationship

Partial cointegration test				Test statistics	P value
H_0^R: residuals series follow a pure unit root (no cointegration)				−8.8400	0.0010***
H_0^M: residual series follow a pure AR[1] process (linear cointegration)				−5.1200	0.0014***
The estimated partially cointegrated long-run relationship between apple futures and spot prices					Parameter (SE)
β (apple spot price $\ln p_t^s$)					0.8212*** (0.0298)
ρ					0.4702*** (0.1322)
σ_M					0.0202*** (0.0028)
σ_R					0.0280*** (0.0021)
Log likelihood					−1 871.3100
R^2_{MR}					0.4130
The permanent component (R_t)		mean	N	t-test (P value)	Wilcoxon rank-sum test (P value)[a]
$\lvert\Delta R_t\rvert$	with contract change	0.0621	27	–	–
	without contract change	0.0145	883	0.0086***	0.0000***
$\lvert R_t - \bar{R}_t\rvert$	> 75th quantile of ΔOI / TV	0.1418	233	–	–
	50th–75th quantile of ΔOI / TV	0.1691	233	0.0025***	0.0008***
	25th–75th quantile of ΔOI / TV	0.1765	234	0.3996	0.2054
	< 25th quantile of ΔOI / TV	0.1822	234	0.4719	0.6923

***$P < 0.01$; [a]due to the non-normal distribution of the concerned variables, Wilconxon rank-sum test is also used to compare their difference of mean values among different groups; β – parameter of the spot price in Equation (1); ρ – parameter of the lagged transient part of the cointegration residual, namely $M_t - 1$; σ – standard deviations of the innovation terms in Equations (3) and (4); M – transient part of the cointegration residual; R – permanent part of the cointegration residual; OI – open interest; TV – trade volume

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

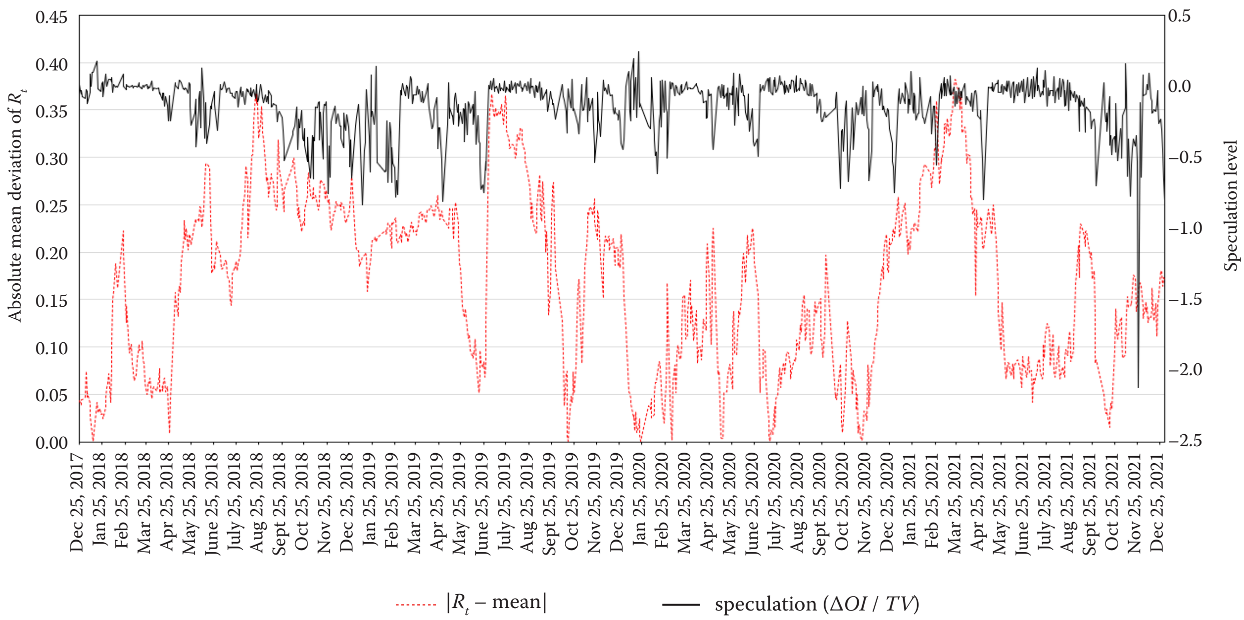

Figure 2. Time-varying absolute mean deviation of R_t and speculation

R_t – permanent part of the partial cointegration residual, see Equations (1) and (2); $\lvert R_t$ – mean$\rvert$ – the absolute mean deviation of R_t (namely, $\lvert R_t - \bar{R}_t\rvert$); speculation ($\Delta OI$ / TV) – the level of speculation in the apple futures market, measured by ΔOI / TV; ΔOI –change of open interests; TV – trade volume of apple futures contracts

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

https://doi.org/10.17221/278/2023-AGRICECON

the basis was not significantly larger when the speculation level was high (see the bottom panel of Table 2). This finding implies that the higher speculation level in the apple futures market tended not to undermine its function.

Time-varying estimates of price discovery. To measure the price discovery function of the apple futures market, we first listed the average values of *PT*, *IS* and *ILS* in Table 3, which are all approximately 0.6. This finding indicates only a moderate dominance of price discovery by the futures market. Compared with the well-established futures markets in China, such as corn and soya beans (Yang et al. 2021), a large share of price discovery function takes place in the apple spot market.

Specifically, we plotted the time-varying *PT*, *IS* and *ILS* measures together in Figure 3, which shows that the apple futures market did not have a lasting dominance of price discovery. Although the three measures moved together, their values varied substantially over the sample period. For instance, they declined rapidly during July 2019 when the spot price increased significantly owing to inventory shortage. The same occurred during each October when fresh apples are harvested and enter the market. In addition, the *PT* measure occasionally was lower than the other two measures. Lower *PT* values suggest a relatively poor efficiency of the apple futures market to avoid transient noise (M_t).

The volatile values of the *PT*, *IS* and *ILS* measures in Figure 3 motivated us to investigate further the possible underlying factors that affect the price discovery function. The sudden decrease of the *PT*, *IS* and *ILS* measures suggests that different futures contracts may function differently. We plotted the *TV* of the apple futures contracts against the *IS* measure in Figure 4, showing that the apple futures market tended to lose its dominance when the *TV* was low. We used a *t*-test and found that the *TV* was significantly higher when *IS* > 0.5 (see the bottom panel of Table 3).

More details about the performance of different apple futures contracts are listed in Table 4, which demonstrates that the price discovery function varied greatly for different futures contracts. In particular, it had poor performance of price discovery for AP11 and AP12 contracts, with their *TV* being low. Given that the AP11 and AP12 contracts correspond to the period of apple harvest (October and November), the poor performance of the apple futures market implies that apple traders tended to focus on the spot market within this period.

Regarding the effect of speculation on price discovery, the speculation level is plotted versus the *IS* measure in Figure 5. The speculation level over the sample period was relatively stable, and its mean value was not significantly different when *IS* < 0.5 and *IS* > 0.5 (see the bottom panel of Table 3). In line with the results drawn from Figure 2 and Table 2, high speculation level did not appear to undermine the price discovery function of the apple futures market. This finding is important because overspeculation has long been blamed as the primary cause of commodity price spikes or even bubbles. Regulators often restrain speculation to protect the proper functioning of futures markets (Etienne et al. 2015). Consistent with previous findings, our re-

Table 3. Average measures of price discovery

Average price discovery			*PT*	*IS*	*ILS*
Futures			0.6113	0.6493	0.6251
Spot			0.3887	0.3507	0.3749
Comparison:		Mean	N^a	*t*-test (*P* value)	Wilcoxon rank-sum test (*P* value)[b]
Trade volume	*IS* < 0.5	4.1938	302	–	–
	IS > 0.5	4.4802	657	0.0001***	0.0002***
ΔOI / *TV*	*IS* < 0.5	–0.1333	292	–	–
	IS > 0.5	–0.1395	641	0.6298	0.9252

***P < 0.01; [a]The number of trade volume and ΔOI / *TV* are different, because we remove the contract change time points when calculating the; [b] due to the non-normal distribution of the concerned variables, Wilcoxon rank-sum test is also used to compare their difference of mean values among different groups; *IS* – time-varying indicator of price discovery function for the apple futures market based on Equation (9); *PT* – time-varying indicator of price discovery function for the apple futures market based on Equation (8); *ILS* – time-varying indicator of price discovery function for the apple futures market based on Equation (10); *OI* – open interest; *TV* – trade volume

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

https://doi.org/10.17221/278/2023-AGRICECON

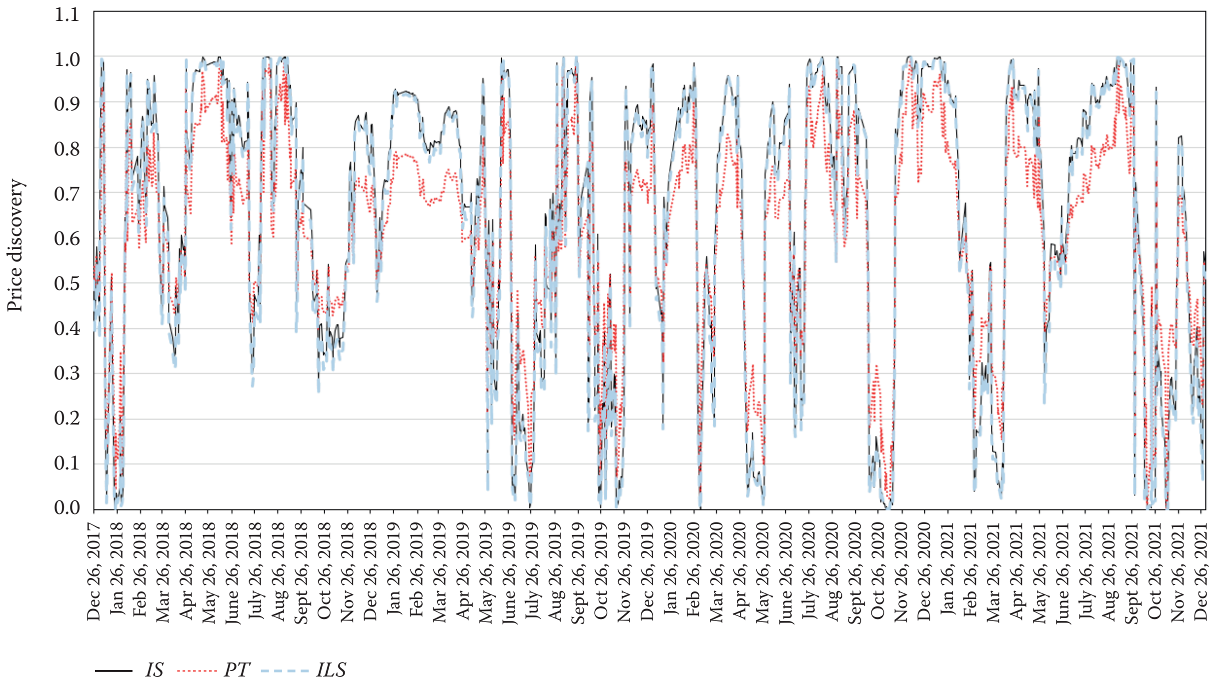

Figure 3. Time-varying measures of price discovery for the apple futures market

IS – time-varying indicator of price discovery function for the apple futures market based on Equation (9); *PT* – time-varying indicator of price discovery function for the apple futures market based on Equation (8); *ILS* – time-varying indicator of price discovery function for the apple futures market based on Equation (10)

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

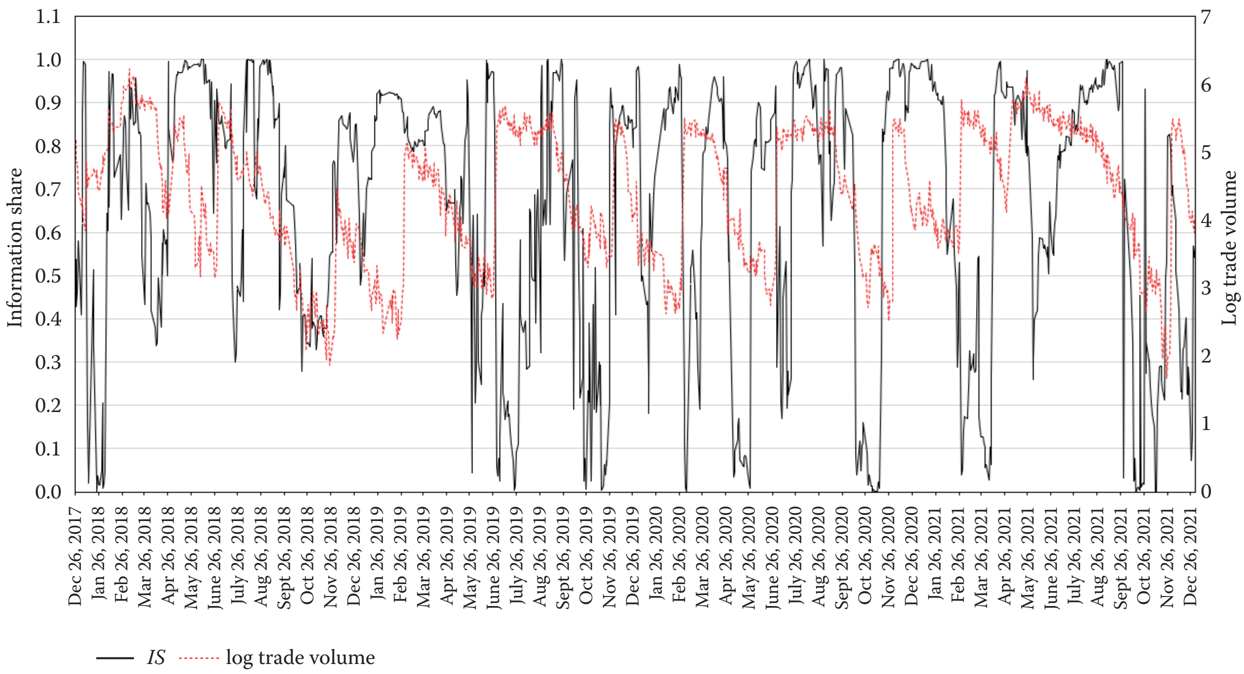

Figure 4. Information share (*IS*) and trade volume

IS – information share, namely the time-varying indicator of price discovery function for the apple futures market based on Equation (9); log trade volume – log (trade volume of apple futures contracts)

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

https://doi.org/10.17221/278/2023-AGRICECON

Table 4. Price discovery for different contracts

Contracts	The ratio of trading days when $IS < 0.5$[a]	Mean trade volume	Mean ΔOI / TV
AP05 : 2018	26/77	5.1522	–0.0143
AP07 : 2018	0/38	4.3222	–0.1064
AP10 : 2018	12/64	4.6323	–0.0862
AP11 : 2018	**13/18**	2.7283	–0.3323
AP12 : 2018	**16/22**	2.4502	–0.3398
AP01 : 2019	0/20	3.8617	–0.3037
AP03 : 2019	2/35	2.9220	–0.3912
AP05 : 2019	0/42	4.6427	–0.1263
AP07 : 2019	11/39	3.4281	–0.2845
AP10 : 2019	**35/65**	5.2912	–0.0259
AP11 : 2019	**13/18**	3.7909	–0.1518
AP12 : 2019	**16/21**	3.7504	–0.1914
AP01 : 2020	1/22	4.8696	–0.1414
AP03 : 2020	9/35	3.2187	–0.1461
AP05 : 2020	13/42	5.0603	–0.0558
AP07 : 2020	17/38	3.4055	–0.1213
AP10 : 2020	11/65	5.2075	–0.0269
AP11 : 2020	**12/14**	3.4131	–0.3254
AP12 : 2020	**11/21**	3.1991	–0.2276
AP01 : 2021	0/23	4.8304	–0.1960
AP03 : 2021	4/33	3.9238	–0.1427
AP05 : 2021	**27/44**	5.1513	–0.1024
AP07 : 2021	5/39	5.6743	–0.0115
AP10 : 2021	1/64	5.0875	–0.0857
AP11 : 2021	**15/16**	3.2924	–0.2950
AP12 : 2021	**17/21**	2.7338	–0.4654
AP01 : 2022	**15/23**	4.7902	–0.1758

[a]we only consider IS measure, because it incorporates both timeliness and efficiency dimensions of price discovery function; bold – ratio of trading days when $IS < 0.5$ is larger than 0.5; IS – information share, namely the time-varying indicator of price discovery function for the apple futures market based on Equation (9)

Source : Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

sults suggest that these policy measures may be inappropriate (Bohl et al. 2020).

Price convergence to the mean spot price or the futures price? The law of one price implies that the prices of the same product sold in different markets would converge to the same level. We used the disaggregated spot price data to test whether the apple futures market improved the price convergence level of different regional markets. Specifically, we tested whether the regional spot prices of apples converged to 'the law of one mean spot price' or 'the law of one futures price'. Higher convergence of regional spot prices to the futures price would imply that the futures market functioned well for improving market integration. The results of the univariate ADF test and MW panel unit root test on the relative price series are listed in Table 5.

On the basis of the ADF test results for each relative price to the mean spot price, we found 15 of 35 markets to have stationary relative price series during the two-year period both before (January 1, 2016–December 21, 2017) and after (December 22, 2017–December 31, 2019) the establishment of the apple future market. This finding is comparable with those of Ceglowski (2003) and Fan and Wei (2006). This number increased to 19 in the next two years (January 1, 2020–December 31, 2021). In contrast, for the relative price to the futures price, only four of 35 markets were stationary

https://doi.org/10.17221/278/2023-AGRICECON

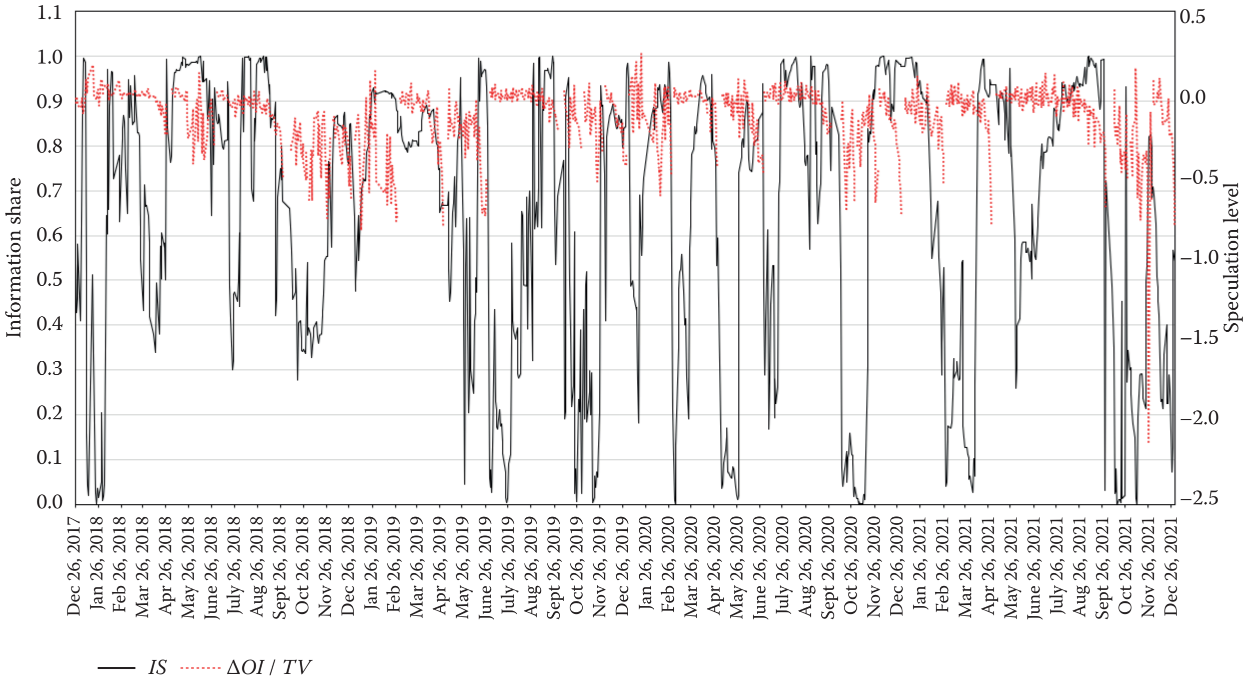

Figure 5. Information share (IS) and speculation

IS – information share, namely the time-varying indicator of price discovery function for the apple futures market based on Equation (9); ΔOI / TV – the level of speculation in the fresh apple futures market; ΔOI – change of open interests; TV – trade volume of apple futures contracts.

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

Table 5. Comparing the spot price convergence levels between different periods

Convergence	Before the futures market (Jan 1, 2016–Dec 22, 2017)	After the futures market (Dec 23, 2017–Dec 31, 2019)	After the futures market (Jan 1, 2020–Dec 31, 2021)
Converge to mean spot price			
Proportion of converging markets (ADF)	15/35	15/35	19/35
Proportion of converging markets (PC)	18/35	19/35	23/35
MW test statistics and significance (panel unit root test)	295.8629***	210.0601***	274.7029***
Converge to futures price			
Proportion of converging markets (ADF)	–	4/35	10/35
Proportion of converging markets (PC)	–	12/35	13/35
MW test statistics and significance (panel unit root test)	–	94.0017**	111.1028***
Observations (days)	709	699 (459)	722 (482)

,* $P < 0.05$ and $P < 0.01$, respectively; ADF – Augmented Dickey-Fuller test; PC – partial cointegration test; MW – panel unit root test developed by Maddala and Wu (1999)

There are only 459 trading days for the apple futures market during the period between Dec 22, 2017 and Dec 31, 2019, and 482 trading days during the period Jan 1, 2020 and Dec 31, 2021.

Source: Own calculations based on ZCE and WIND Database (WIND 2022; ZCE 2022)

https://doi.org/10.17221/278/2023-AGRICECON

during the first two years of the apple futures market (December 22, 2017–December 31, 2019), increasing to 10 in the next two years (January 1, 2020–December 31, 2021).

Moreover, the results of the MW test rejected the null hypothesis of a panel unit root for all subsample periods, whereas the values of the MW test statistics for the relative prices to the futures price were much smaller. All of these results show that regional spot prices were more likely to converge to their own mean value than to the futures price. We further used the partial cointegration method to estimate the stationarity of the relative price series – namely, whether the residuals between the original regional spot price P_{it} and $\bar{P}_t$ (FP_t) contained a permanent (random walk) part and a transient (mean reverting) part. Compared with the results based on the ADF test, more regional spot price series were partially cointegrated with the benchmark $\bar{P}_t$ or FP_t. Nevertheless, our main result remains: the regional spot prices were more likely to converge to their own mean value than to the futures price. Because of high storage and delivery costs, commercial traders in the apple supply chain tend to focus more on the spot market than on the futures market. This finding is in line with the limited dominance of price discovery indicated by the time-varying measures.

CONCLUSION

Agricultural futures contracts serve as an increasingly important tool to improve agricultural market efficiency. However, the function of futures markets for agricultural perishables has long been in doubt. In this study, we aimed to analyse the performance of the fresh apple futures market in China, which is the world first futures contract for fresh fruits. Since its establishment, the apple futures market has attracted tremendous trading. A comprehensive evaluation of this new futures market not only contributes to the literature on agricultural futures market but also provides useful policy implications for emerging economies, most of which are price takers for agricultural commodities and aim to manage price risks through domestic futures markets. If the apple futures market functions as a useful tool of price discovery, risk sharing and market integration, it would dominate the price discovery process and improve the convergence level of regional spot prices.

Our results obtained from the combination of partial cointegration with state-space modelling illustrate a time-varying price discovery process for the apple futures market. Specifically, we found only a limited dominance of the apple futures market in the price discovery process. Higher TV tended to coincide with higher dominance of the apple futures market, and we found no evidence to support the point that active speculation undermines the price discovery function.

Moreover, the law of one price suggests that, for an integrated market, the prices of the same product sold in different marketplaces would converge to the same level. We used the disaggregated apple price series of different regional markets in China to estimate their convergence level toward different benchmarks – namely, the mean spot price and the futures price. Our results show that regional spot prices tended to converge to their own mean spot price over time rather than to the apple futures price. Because of high storage and delivery costs, the participants in the apple supply chain tended to pay more attention to the spot market, which is in line with the limited dominance of the apple futures market in the price discovery process.

Overall, we can conclude that the newly established futures market for fresh apples in China does not function very well in terms of price discovery and market integration. This finding may further undermine its ability to transfer price risks from commercial traders to speculators. Spot markets are still quite important for price discovery. Constraints on speculation are not a proper way to improve the efficiency of the futures market, and more commercial traders should be encouraged to participate in futures trading. Furthermore, the establishment of new futures markets for agricultural perishables should be approached with caution. The evidence on efficient futures markets for storable commodities cannot be used to justify the establishment of futures markets for agricultural perishables.

Finally, our conclusion is limited due to the lack of more specific data on the storage and delivery costs of different marketplaces, as well as the apple farmers' attitudes toward the futures market. For future research, more specific data on the spot markets of agricultural perishables may provide a better insight on the limited function of the corresponding futures markets.

REFERENCES

Adämmer P., Bohl M.T. (2018): Price discovery dynamics in European agricultural markets. Journal of Futures Markets, 38: 549–562.

Ankamah-Yeboah I., Nielsen M., Nielsen R. (2017): Price formation of the salmon aquaculture futures market. Aquaculture Economics and Management, 21: 376–399.

https://doi.org/10.17221/278/2023-AGRICECON

Baillie R.T., Booth G.G., Tse Y., Zabotina T. (2002): Price discovery and common factor models. Journal of Financial Markets, 5: 309–321.

Bohl M.T., Siklos P.L., Stefan M., Wellenreuther C. (2020): Price discovery in agricultural commodity markets: Do speculators contribute? Journal of Commodity Markets, 18: 100092.

Bohl M.T., Stephan P.M. (2013): Does futures speculation destabilize spot prices? New evidence for commodity markets. Journal of Agricultural and Applied Economics, 45: 595–616.

Bohl M.T., Sulewski C. (2019): The impact of long-short speculators on the volatility of agricultural commodity futures prices. Journal of Commodity Markets, 16: 100085.

Brenner R.J., Kroner K.F. (1995): Arbitrage, cointegration, and testing the unbiasedness hypothesis in financial markets. Journal of Financial and Quantitative Analysis, 30: 23–42.

Brorsen B.W., Fofana N.F. (2001): Success and failure of agricultural futures contracts. Journal of Agribusiness, 19: 129–145.

Ceglowski J. (2003): The law of one price: Intranational evidence for Canada. The Canadian Journal of Economics / Revue canadienne d'Economique, 36: 373–400.

Clegg M., Krauss C. (2018): Pairs trading with partial cointegration. Quantitative Finance, 18: 121–138.

Dimpfl T., Flad M., Jung R.C. (2017): Price discovery in agricultural commodity markets in the presence of futures speculation. Journal of Commodity Markets, 5: 50–62.

Enders W., Lee J. (2012): A unit root test using a Fourier series to approximate smooth breaks. Oxford Bulletin of Economics and Statistics, 74: 574–599.

Etienne X.L., Irwin S.H., Garcia P. (2015): Price explosiveness, speculation, and grain futures prices. American Journal of Agricultural Economics, 97: 65–87.

Fan C.S., Wei X. (2006): The law of one price: Evidence from the transitional economy of China. Review of Economics and Statistics, 88: 682–697.

FIA (2021): 2020 annual trends in futures and options trading. Available at https://www.fia.org/sites/default/files/2021-01/2020%20annual%20trends%20in%20futures%20and%20options%20trading_%2027%20January%202021%20Distribution.pdf (accessed Apr 13, 2021).

Gregory A.W., Hansen B.E. (1996): Tests for cointegration in models with regime and trend shifts. Oxford Bulletin of Economics and Statistics, 58: 555–560.

Gonzalo J., Granger C. (1995): Estimation of common long-memory components in cointegrated systems. Journal of Business and Economic Statistics, 13: 27–35.

Hasbrouck J. (1995): One security, many markets: Determining the contributions to price discovery. The Journal of Finance, 50: 1175–1199.

Hu Z., Mallory M., Serra T., Garcia P. (2020): Measuring price discovery between nearby and deferred contracts in storable and nonstorable commodity futures markets. Agricultural Economics, 51: 825–840.

Huchet N., Fam P.G. (2016): The role of speculation in international futures markets on commodity prices. Research in International Business and Finance, 37: 49–65.

Lien D., Shrestha K. (2009): A new information share measure. Journal of Futures Markets, 29: 377–395.

Lucia J.J., Pardo A. (2010): On measuring speculative and hedging activities in futures markets from volume and open interest data. Applied Economics, 42: 1549–1557.

Maddala G.S., Wu S. (1999): A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and Statistics, 61: 631–652.

Milgrom P. (2017): Discovering Prices: Action Design in Markets with Complex Constraints. New York, Columbia University Press: 248.

Mohanty S.K., Mishra S. (2020): Regulatory reform and market efficiency: The case of Indian agricultural commodity futures markets. Research in International Business and Finance, 52: 101145.

Perera D., Białkowski J., Bohl M.T. (2020): Does the tea market require a futures contract? Evidence from the Sri Lankan tea market. Research in International Business and Finance, 54: 101290.

Perron P. (1989): The great crash, the oil price shock, and the unit root hypothesis. Econometrica, 57: 1361–1401.

Pindyck R.S. (2001): The dynamics of commodity spot and futures markets: A primer. The Energy Journal, 22 (3), 1–29.

Putniņš T.J. (2013): What do price discovery metrics really measure? Journal of Empirical Finance, 23: 68–83.

Rittler D. (2012): Price discovery and volatility spillovers in the European Union emissions trading scheme: A high-frequency analysis. Journal of Banking and Finance, 36: 774–785.

Sanders D.R., Manfredo M.R. (2002): The white shrimp futures market: Lessons in contract design and marketing. Agribusiness, 18: 505–522.

Singh K.M. (2012): Overview of futures trading in agricultural commodities: A conceptual perspective. SSRN Electronic Journal: 6.

Van Huellen S. (2018): How financial investment distorts food prices: Evidence from U.S. grain markets. Agricultural Economics, 49: 171–181.

Vollmer T., Herwartz H., Von Cramon-Taubadel S. (2020): Measuring price discovery in the European wheat market using the partial cointegration approach. European Review of Agricultural Economics, 47: 1173–1200.

WIND (2022): Qianhai wholesale price index for red fuji apples. Available at https://www.wind.com.cn/ (accessed Nov 1, 2022).

Working H. (1948): Theory of the inverse carrying charge in futures markets. Journal of Farm Economics, 30: 1–28.

https://doi.org/10.17221/278/2023-AGRICECON

Yan B., Zivot E. (2010): A structural analysis of price discovery measures. Journal of Financial Markets, 13: 1–19.

Yang J., Bessler D.A., Leatham D.J. (2001): Asset storability and price discovery in commodity futures markets: A new look. Journal of Futures Markets, 21: 279–300.

Yang J., Li Z., Wang T. (2021): Price discovery in Chinese agricultural futures markets: A comprehensive look. Journal of Futures Markets, 41: 536–555.

ZCE (2018): Materials on Apple Futures Market. Available at http://www.czce.com.cn/cn/uploadfile/2018/08/20/20180820222620226.pdf (accessed June 29, 2020; in Chinese).

ZCE (2022): Fresh apple futures price. Available at http://english.czce.com.cn/en/MarketData/HistoricalData/H810217index_1.htm (accessed Nov 1, 2022).

Received: August 23, 2023
Accepted: November 20, 2023
Published online: December 15, 2023