International Market Integration under WTO: Evidence in the Price Behaviors of Chinese and US Wheat Futures

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Abstract

China’s 10-year-old wheat futures market, the China Zhengzhou Commodity Exchange (CZCE) has been in stable development since establishment and is expected to be integrated to the world market after China joined WTO. This paper compares the price behavior of CZCE with that of the Chicago Board of Trade (CBOT) in the US using ARCH/GARCH based univariate and multivariate time series models for the period between 1999 and 2003, around when China joined the World Trade Organization (WTO). Results show both markets can be modeled by an ARCH(1) or a GARCH(1,1), and the models have better fit when conditional error variance is t distributed. The price series in CZCE and CBOT are interrelated but not cointegrated. The existing interrelations between the two markets are significant and asymmetric, where CBOT holds a dominant position in the interactions while CZCE is more like a follower.

Classification Code: G15 Q14

Key words: integration, wheat, futures price, GARCH, China
I. Introduction

The prosperity of wheat trading in world’s major commodity futures markets has provided an effective channel for market participants to hedge price risks and insure profits (Yang and Leatham, 1999). If the futures market is efficient, price will reflect the equilibrium level in the spot market, and will help the formation of a rational market expectation of price in both the short run and the long run. China is the biggest wheat production and consumption country in the world (USDA, 2004). Wheat production, consumption and trade account for a major share of China’s food system. In 2002, the share of wheat in all grains is 27.0%, 28.9%, and 32.9% for production, consumption, and imports, respectively.

Agricultural commodity futures markets emerged in China in the early 1990’s, when China was stepping into an advanced phase of its market-oriented economic reform. China’s first exchange market, the China Zhengzhou Commodity Exchange (CZCE) was founded in 1990. Wheat futures trading started in May 1993. CZCE is the only exchange trading wheat futures contracts in the country today. In 1999, CZCE accounted for 50% in total trading value and 49% in total trading volume of all commodity exchanges in China. Since 1997, the trading of wheat futures has experienced a stable growth except for 1999 (Figure 1) In 2003, the total trading value amounted to 796.1 billion Yuan² and total trading volume was 49.1 million contracts.

After about 10 years of development, the wheat futures price in CZCE is on the way to becoming an important indicator of China’s wheat price. The correlation between the spot price and futures price is as high as 0.96 and a strong association is identified between the wheat futures price of CZCE and that of Chicago Board of Trade (CBOT) in the United States (CZCE Report,
China’s wheat futures price became more important to the world after November 2001 when China obtained full membership in the WTO. Since then, China has entered a fast lane to merging to the world market. Capital, technology, and information flow and exchange between domestic and world markets have become more frequent than ever as China started to open domestic markets, including agricultural product markets. However, for wheat market the opening is in a slow process. Unlike the completely open corn markets, the quota for wheat import still exists.

Given the enhanced interrelation between China’s markets and the world market, China’s integration to the world is on the way and has shown impacts on two sides. Facing challenges from major wheat exporters such as the US and Canada, China’s previously over-valued domestic wheat price is expected to undergo a downward shift, which will probably first show up in the futures prices. Meanwhile, the futures price in CZCE may become more volatile due to the stronger linkage to the world commodity markets and the unpredictable factors in the world economy, or less volatile because some irrational behavior of domestic traders that had a fairly strong influence on prices in the past (Durham and Si, 1999) will not be able to affect an integrated world market price.

Founded in 1848 and by far the largest and most developed agricultural commodity market in the world, the CBOT in the US has been playing a leading role in the world commodity market. The wheat futures price in CBOT is highly volatile and directly reflects the supply and demand in both US and world markets. It has been one of the most important wheat price indicators in the world market. In this paper, the CBOT wheat futures market is chosen to represent the world market and the integration of CZCE to the CBOT will be analyzed as an approximation of CZCE’s integration to the world market.
This research is a quantitative assessment of China’s wheat futures price performance and the integration of China’s wheat futures market to the world market. The objective is to identify the best time series models to characterize the price behaviors in both CZCE and CBOT, and the interrelationship between them. We then use the identified models to compare the price patterns in both markets and investigate the outlook of China’s market integration to the world market. Specifically, this analysis will: 1) estimate and identify an appropriate ARCH/GARCH model for China’s and US’ wheat futures prices; 2) investigate the interrelations between the two price series, including cointegration in the first moment and autoregressive heteroskedasticity in the second moment, in a multivariate framework; and 3) compare the estimations between the two markets and assess the role of China’s wheat futures market in the world market.

II. Previous Studies

Since 1980s, China’s successful economic reform has drawn the whole world’s attention for more than two decades, and the membership to the World Trade Organization (WTO) enhanced such attention to a new level. However, studies on China’s agricultural commodity futures markets are quite limited, particularly with regard to wheat futures. Moreover, most of existing studies are more of descriptive analyses on regulatory and market development issues rather than quantitative investigations of futures prices. Such studies include Tao and Lei (1998); Fan, Ding and Wang (1999); and Zhu and Zhu (2000). A historical perspective on the development of China’s futures market is shown in Yao (1998), which includes a detailed structural analysis of the commodity futures markets and the government’s legislative and regulatory attempts.

Some quantitative analyses have been attempted in recent years. Williams, et al. (1998) investigated mung bean trading in CZCE to test for market efficiency. Durham and Si (1999)
examined the relationship between the China Dalian Commodity Exchange (CDCE), another commodity futures market in China, and the CBOT soybean futures prices through a regression model. Wang and Ke (2003) investigated the information efficiency of the CZCE wheat and CDCE soybeans futures in a framework of cointegration between cash and futures markets. Despite that, quantitative studies dealing with the time series properties of price on China’s wheat futures market, especially on the issue of world market integration, have not been found.

Modeling time series data usually start from the moving average (MA) model, autoregressive (AR) model, or more generally, autoregressive integrated moving average (ARIMA) model for the first moment of the data. However, stochastic trend or unit root is discovered as a characteristic property of many high frequency commodity price series (Ardeni 1989; Baillie and Myers, 1991). More complete but complicated price models focusing on the second- or higher-order moment variability were introduced in early 1980s and have enjoyed great attention in the last two decades. The autoregressive conditional heteroskedasticity (ARCH) model, developed by Engle (1982), allows the shocks in nearby earlier periods to affect the current volatility. The generalized ARCH, (GARCH) model (Bollerslev, 1986) allows, in addition, previous volatilities to affect current volatility, so that the volatility behaves like an AR process. ARCH and GARCH models have been widely applied in financial time series analysis (Bollerslev, Cho, and Kroner, 1992) as well as in agricultural commodity prices (Bailie and Myers, 1991; Yang and Brorsen, 1992; Tomek and Myers, 1993; Myers, 1994). Excess kurtosis, namely heavier tails compared to normal distribution, is also found in commodity prices (Gordon, 1985; Deaton and Laroque, 1992; Myers, 1994).

Although ARCH and GARCH models can partially alleviate the excess kurtosis problem (Engle, 1982; Myers, 1994), empirical studies have shown that they cannot capture all of it if the
normal distribution is assumed on the price innovations (Bollerslev, 1987; Baillie and Myers, 1992; Yang and Broersen, 1992). One possible solution to this problem is to use t-distribution instead of normal distribution to describe the price innovations in the ARCH/GARCH model (Myers, 1994).

In the context of multivariate analysis, time-series of variables are often inter-related. Based on the theoretical framework derived by Engle and Granger (1987), and the empirical test methods by Johansen and Juselius (1990, 1992), studies on international futures markets have started to focus on using cointegration as an indication of market integration. Cointegration is a phenomenon that multiple nonstationary variables are driven by some common stochastic trends. Yang, Zhang, and Leatham (2003) examined the price and volatility transmission in a three-variable system for the US, Canadian, and EU markets. They found no cointegration in the system. Bessler, Yang, and Wongcharupan (2003) examined the wheat futures markets in the US, Canada, Australia, EU, and Argentina, and found cointegration.

The present paper contributes to the existing literature on China’s wheat futures prices in two ways. First, it incorporates both China’s and US’s wheat futures markets into a multivariate time series model so that the price interactions in the two markets can be studied simultaneously. Second, besides the interaction at the mean level as investigated in the cointegration studies, the interaction at the variance level is also carefully examined. Third, the assumed conditional error distribution of price changes is extended from normal distribution to t-distribution in a multivariate situation; therefore improvement of excess kurtosis can be examined and compared.

III. Models

1. Univariate Conditional Heteroskedastic Models
We start with the univariate ARCH and GARCH models, which allow the volatility of error terms to change over time. An ARCH($q$) model is commonly defined to include a mean equation

$$Y_t = X_t' \beta + \varepsilon_t, \text{ where } \varepsilon_t | \Omega_{t-1} \sim (0, h_t)$$

and a variance equation

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$$

where $Y_t$ denotes the dependent variable; $X_t$ denotes the vector of explanatory variables which can include a constant, a time trend, lagged dependent variables, and/or any (lagged) exogenous variables; $t$ denotes the time period; $\varepsilon_t$ is the error component in the ARCH model whose conditional distribution has a zero mean and time-varying variance $h_t$; $\Omega_{t-1}$ is the information set available at $t-1$; $\beta$ is the parameter vector for the exogenous variables; $\omega (\omega > 0)$ is the parameter for intercept in the variance equation; and $\alpha_i ( \alpha_i \geq 0 \text{ and } \sum_{i=1}^{q} \alpha_i < 1)$ for $i = 1, 2, ..., q$ is the parameter for ARCH effect. $\varepsilon_t$’s are serially uncorrelated, however, their dependency lies on the second moment evolution.

A GARCH ($p, q$) model is defined in the same way except that

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}$$

with $\gamma_j$ for $j = 1, 2, ..., p$ as additional parameters for past volatilities; $\omega > 0, \alpha_i, \gamma_j \geq 0$ and $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \gamma_j < 1$. 
The basic ARCH\((q)\) model is a short memory process in that only the most recent \(q\) shocks have an impact on the current volatility. The GARCH\((p, q)\) model is a long memory process, in which all the past shocks can affect the current volatility indirectly through the \(p\) lagged variance terms.

### 2. Multivariate Conditional Heteroskedastic Models

Multivariate ARCH and GARCH models allow more than one series to be modeled together so that the interrelation between different series can be examined and tested through cross equation parameter constraints.

An \(m\)-variate GARCH\((P, Q)\) model can be defined as:

\[
Y_t = BX_t + \epsilon_t, \quad \epsilon_t | \Omega_{t-1} \sim (0, H_t)
\]

\[
H_t = W + \sum_{i=1}^{Q} A_i (\epsilon_{t-i} \epsilon_{t-i}') A_i' + \sum_{j=1}^{P} \Gamma_j H_{t-j} \Gamma_j'
\]

where \(Y_t\) is now an \(m \times 1\) dependent variable vector; \(B\) is the coefficient matrix corresponding to the explanatory variable vector \(X_t\); \(\epsilon_t\), the error vector, is conditionally distributed with a mean of an \(m \times 1\) null vector and an \(m \times m\) variance-covariance matrix \(H_t\); \(W\) is an \(m \times m\) parameter matrix for the constant terms, and \(A_i\) and \(\Gamma_j\) are \(m \times m\) parameter matrices for GARCH coefficients. By definition, the ARCH\((Q)\) model is a special case of the GARCH\((P,Q)\), when the coefficient matrices for the past variance-covariance matrices, \(\Gamma_j\)'s, are set at zeroes.

Alternative definitions of the variance equations and restrictions on matrices \(A_i\) and \(\Gamma_j\) exist, which lead to different versions of multivariate ARCH/GARCH models. The above defined model allows each element of the current variance-covariance matrix \(H_t\) to be affected by all elements of the past variance-covariance matrices and/or the squared error matrices. This is called
BEKK model (Engle and Kroner, 1995). Other commonly used models, like constant conditional correlation (CCC) model (Bollerslev, 1990) and the diagonal-vec (DVEC) model (Bollerslev, Engel, and Wooldridge, 1988), have simpler forms with different assumptions on parameters.

The variance equation in a CCC model has the following form:

\[(4')\]
\[
\begin{align*}
    h_{m,n,t} &= \omega_m + \sum_{i=1}^{q} \alpha_{m,n} \varepsilon_{m,t-i}^2 + \sum_{j=1}^{p} \gamma_{m,n} h_{m,n,t-j} \\
    h_{m,n,t} &= \rho_{mn} \sqrt{h_{m,m,t} h_{n,n,t}}, m \neq n
\end{align*}
\]

where \( h_{m,n,t} \) is the \( mn \)th element in \( H_t \), and \( \rho_{mn} \) is the constant correlation between \( h_{m,m,t} \) and \( h_{n,n,t} \).

With an imposed constant correlation coefficient to the independent univariate ARCH/GARCH models, the CCC model largely reduces the number of parameters to be estimated. However, this model only allows the conditional variances to evolve based on their own past levels and past shocks, and the relationship between one another, is constrained to null and cannot be revealed.

The DVEC model defines the variance equation as:

\[(4'')\]
\[
    H_t = W + \sum_{i=1}^{Q} A_i \odot (\varepsilon_{t-i} \varepsilon_{t-i}') + \sum_{j=1}^{P} \Gamma_j \odot H_{t-j}
\]

where \( \odot \) is the Hadamard product operator, i.e. element-by-element multiplication. \( A_i \) and \( \Gamma_j \) are restricted to be symmetric matrices. This model is called the diagonal-vec (DVEC) model which allows each element of the current variance-covariance matrix \( H_t \) to be affected only by its own past values and/or corresponding element in the past squared error matrices. Similar to the CCC model, information about the relationships between variances of different series is not available in DVEC form. Furthermore, when the parameter matrices are set to be diagonal, the model will degenerate into separate univariate models.

8
Data Description

To study the price behaviors of the two wheat futures markets, we collected daily settlement price series for the September wheat contracts on both CZCE and CBOT from January 4, 1999 to September 12, 2003. There are 1182 observations in total. The CZCE price data are downloaded from CZCE’s online database at http://www.czce.com.cn. The CBOT data are collected from http://www.turtletrader.com and by purchase. The prices are taken as continuous for each trading day. In order to catch the possible WTO effect in the analysis, we break the whole price set into three different, that is, pre-WTO period (January 4, 1999 to January 3, 2001), post-WTO period (September 21, 2001 to September 12, 2003), and transition period (January 4, 2000 to September 13, 2002). The reason for the division lies in that this can help us extract the influence of WTO on the market evolution, especially of CZCE, during the whole time range. As 2001 is the year when China joined WTO, the price behaviors for that year may contain a lot of transitions. Therefore we exclude it from the pre-WTO and post-WTO analyses. But we include it in the transition period analysis. Results from the three different sets of estimation and tests can also help examine the robustness of model selection and estimation.

A switching contract dummy variable, $SD_t$, is introduced in the explanatory variable vector $\mathbf{X}$ in addition to the constant term for both series to indicate when the price series switches from an old contract to a new one. The switching points are set at the last trading day of the old contract following the method as in Myers and Hanson (1993). $SD_t$ equals 1 at the switching points and 0 otherwise.

The time-series plots of CZCE and CBOT prices are given in Figure 2. Both series show strong nonstationarity and stochastic trend, while CZCE prices look more chaotic than CBOT prices. For both price series, the sample autocorrelation functions show very slow exponential
decay, and the sample partial autocorrelation functions show a large spike in the first lag. The augmented Dickey-Fuller (ADF) unit root test yields a P value of 0.55, 0.60, and 0.63 for pre-WTO, transition, and post-WTO CZCE prices; A P value of 0.63, 0.90, and 0.75 for pre-WTO, transition, and post-WTO CBOT prices, respectively. The results confirm the existence of unit root. Therefore, first difference is taken for both CZCE and CBOT prices.

From the time series plots (Figure 3) of the squared first difference data, evidence of a time-varying volatility pattern is visible in CBOT series. That is, big changes are often followed by other big ones and small changes followed by small ones. This pattern is consistent with the ARCH/GARCH processes. Furthermore, the P values of Portmanteau $Q$ statistic and the LaGrange Multiplier statistic, for testing $H_0$: no ARCH effect, are computed. For CZCE price changes, the ARCH effect is evident at 95% level in the second six lages among lag 1 to 12 during the pre-WTO period, not statistically significant during transition period, and strong evident in first twelve lags during the post-WTO period. For CBOT price changes, the effect exists in all twelve lages during the pre-WTO period, strongly exists during the transition period, and not significantly exists in the post-WTO period. Normality check of CZCE and CBOT price changes implies strong evidence against normality. All normality tests reject the null hypothesis of normality with a P value less than or equal to 0. For CBOT, the kurtosis coefficient is 2.23, 1.80, and 18.61 for pre-WTO, transition, and post-WTO, respectively, indicating the distribution has fatter tails than the normal distribution. Correspondingly, the skewness coefficient is $-0.0014$, 0.24, and 2.02, meaning it is quite symmetric and much closer to the benchmark of zero relative to the kurtosis. The distribution of CZCE price changes is also quite symmetric with the skewness coefficients of $0.93$, -0.57, and $-1.71$ for pre-WTO, transition, and post-WTO periods, respectively, but even fatter tails. The corresponding kurtosis coefficients are 11.80, 6.67, and
10.16. These coefficients indicate the non-normality is mostly caused by excess kurtosis rather than the skewness.

IV. Results

1. Univariate Analysis

In this section, we study the price performances of CZCE and CBOT separately. Due to the existing unit root, first differences of the data are fit into alternative time series models. The mean equation of the model is defined as price change dependent on the constant term and the contract switching dummy, $SD$. A univariate framework is applied to find the best specifications of ARCH/GARCH process. The GARCH procedure in GARCH module of S-PLUS is used to estimate these models. For the visible heavy tails of the price distributions, we estimate price models under both normality and t distributions. Results based on the two distributions are examined and compared.

Selection of Model Specification

Alternative specifications in terms of the lags of the ARCH/GARCH models are fitted. Two goodness-of-fit criteria, Akaike Information Criterion (AIC) and Schwarz’s Bayesian Information Criterion (BIC), along with significance criterion, are used in coordination to select the best model. The model fitting results show that under the normality assumption, ARCH(1) for pre-WTO CZCE price changes, GARCH(1,1) for pre-WTO CBOT price changes, and ARCH(1) has the best fit for both CZCE and CBOT price changes during the transition period. ARCH/GARCH model doesn’t fit for the post-WTO CZCE and CBOT price changes.

In the estimation of above models, however, the Shapiro-Wilk and Jarque-Bera statistics for normality test reject the normality assumption in all cases. It confirms what we observe in the earlier normality check in the data section, and implies change of distribution relevant and
necessary. Following the existing empirical literature, we assume the error terms in the mean equation is t distributed, i.e. $\epsilon_t \sim t(\nu)$, where $\nu$ denotes the degree of freedom, and with mean 0 and variance $h_t$. With obvious gain in the goodness-of-fit, the best models under t distribution are ARCH(1) for CBOT and GARCH(1,1) for CZCE during transition period. For the pre-WTO and post-WTO period, however, no ARCH/GARCH estimation is convergent. The results are not reported in the paper, but are available from authors upon request.

*Estimation*

Table 1 gives the estimation results of the choice models for CZCE and CBOT during the transition period under both normal and t assumptions. In general, the significance and sign of each parameter are consistent between the two sets of results. The main difference lies in the magnitude, or weight, of the estimated coefficients in the mean and variance equations. The models capture more contract switching and ARCH/GARCH effects when the conditional distribution is t.

From the results based on transition period data, we see both CZCE and CBOT price changes contain no drift. The contract switching has insignificant and negative effects on CBOT price changes, but a significant and positive contribution to CZCE price changes, indicating a jump-up of the price from the mean at the switching point in CZCE. In all the ARCH(1) models for CBOT and CZCE, the ARCH coefficient has a significant but relatively weak impact on the variance, compared with the intercept term. In the GARCH(1,1) for CZCE under t, however, the influence from the intercept reduces enormously. Both GARCH and ARCH coefficients are significant, and GARCH coefficient is a lot more influential, implying a large part of the current volatility in CZCE is due to the last period volatility.
Estimates from pre-WTO price changes under normality have similar pattern for CZCE but different for CBOT when compared with the transition period. In CZCE, the drift in mean of –1.68 is still not significant and the contract switching effect is also positive and significant, but a little less in magnitude as 231.18. The drift in the volatility has a significant and much larger factor of 403.32. The ARCH effect is still significant and has a bigger weight of 0.23. In CBOT, the difference is mainly contributed to the contract-switching variable becomes significant with a positive coefficient of 174.35, showing evident jump-up in prices when contract switches. Although GARCH(1,1) fits the data best, but the effect from the GARCH variable is not significant, implying that influence from last period shocks still plays a major role in the current volatility.

2. Multivariate Analysis

Multivariate analysis allows both price series to be estimated simultaneously. As a result, cross market relations that are unable to be detected in univariate analysis can now be captured. In our multivariate version of the models, the mean equation still follows the same structure as in univariate case, but the variance equation becomes a system of equations.

Cointegration test

In order to identify the possible interrelations that exist in the comovement of the price levels, we first conduct the cointegration test on the original prices of CZCE and CBOT wheat futures, before moving to examine the second moment (volatility) relation. According to the ADF unit root test, both price series are integrated to order one, satisfying the conditions for cointegration test. Proceeding with the Johansen’s cointegration test, however, we fail to reject the null hypothesis of no cointegration during all periods. Results indicate our data on CZCE and CBOT wheat futures prices have no cointegrating relation on the first moment; therefore a vector
regression model is appropriate for the following time series analysis. Here the dependent variable vector is the first difference of prices, and the independent variable vector includes constant and two contract switching dummy variables. Again, the results can be made available upon request.

Selection of Model Specification

To fully disclose the interrelations between CZCE and CBOT wheat prices, we apply three types of multivariate GARCH models, BEKK, CCC, and DVEC, to estimate the CBOT-CZCE bivariate series under both normal and t distributions. By definition, the BEKK model contains information about the cross-market ARCH/GARCH effects. The CCC and DVEC models are simplified multivariate GARCH models with different model structures. Since these two models have different ranks in restrictiveness and robustness, we include both in the estimation for a comparison purpose. The MGARCH procedure in the GARCH module of S-PLUS is used for analysis in this section. The results show that for transition period, GARCH(1,1) in DVEC form and CCC form has better fit under both normal and t distributions, while in BEKK form ARCH(1) performs better (Table 2). For pre-WTO and post-WTO periods, however, results are limited to a few estimable models, such as ARCH(1)-CCC for pre-WTO period. Convergence problem seems much worse in estimation for price behaviors during these periods. For instance, the DVEC model is not fitful for pre-WTO price changes either under normal or t distribution. In the following we will mainly focus on analyzing the estimation results from transition period.

Estimation

Information about the interactions between elements in the conditional variance matrix and relationships between the price changes of China’s and US’ wheat futures during the transition period are now reflected in the estimates (Table 2).
When BEKK model is fitted with normal distribution, CZCE price changes appear to have a small drift while CBOT data do not. The coefficient matrix $\Lambda$ for the switching dummy vector provides full information about within and cross equation relationships of contract switching in the two markets. For own market effect, the CZCE switching dummy has a significant positive impact on the mean of price changes, similar to the univariate case. The CBOT dummy has a significant positive impact on its price changes, quite different to the univariate case. The cross effects, however, are both statistically insignificant, implying the interactions of contract switching between the two markets are weak.

The variance equation estimates, noteworthily, do not directly reflect within- and cross-market effects on volatilities. Those effects can only be shown by certain combinations of these estimates. In the Appendix we provide a detailed derivation of such combinations. The calculated estimated effects are reported in Table 3. When normal distribution is assumed, current volatility of CBOT price changes is positively correlated with the last period shocks in its own market and that in CZCE. The own market effect of 0.1132 dominates the cross market effect by a ratio of 15:1. Therefore the volatility in CBOT is mostly affected by the previous shock in its own market. The previous shock in CZCE has very limited influence on the volatility in CBOT. The volatility in CZCE is even more dominated by own market effect rather than cross market effect. The ratio increases to 28:1.

The insignificance of both $A_{uv}$ and $A_{vu}$ indicates that the cross impact in the variance equation may not exist, and the BEKK is not superior to DVEC or CCC. The smaller AIC’s and BIC’s of DVEC and CCC also indicate they actually have a better fit.

From Table 3, in the bivariate DVEC form of GARCH(1,1), when the underlying conditional distribution is normal, the intercepts in the mean equation are consistent with the
univariate cases, i.e. neither of the series shows significant drift in prices. The own market contract switching dummies have a similar pattern as in the BEKK model. The cross equation terms, more informatively, show that the contract switching in CBOT has significant negative influence on the price changes in CZCE, while switching in CZCE does not affect CBOT price significantly. Since the contract switching dates are different for CBOT and CZCE, around September 15 for CBOT, and one week later for CZCE. This implies when the old contract expires at CBOT, the switching to new contract in CBOT enhances the decreasing trend of old contract prices in CZCE. But the contract switching in CZCE doesn’t have comparable effect on CBOT new contract prices when it is one week after.

In the variance equation, only CZCE volatility has a significant drift. For CBOT price changes, the last period volatility has much more influence on current volatility than last period shock, which indicates CBOT price has a long memory. The former has an estimated coefficient of 0.96 while the latter only has 0.03. The own market effect of volatility for CZCE price changes shows similar pattern. The gap between the influences of last period volatility and last period shock seems smaller in CZCE. This indicates that CZCE price has a shorter memory than CBOT, so that a shock tends to have a larger impact on price of next period in China. That in a certain way indicates prices in CZCE are apt to be more volatile, even chaotic.

Estimation results from CCC model are mostly very close to those from DVEC. In terms of model fitting, the DVEC under normal distribution outperforms both CCC and BEKK with smallest AIC and BIC.

When the underlying distribution is t, results are different. Especially, all the parameters for interaction terms between the two markets, including the switching dummy and covariance, are insignificant. This may indicate the two markets do not demonstrate significant interactions.
Market Integration of CZCE

The integration of CZCE to the world market, especially the CBOT, has been an interesting issue to many researchers as well as government officials since the establishment of CZCE. Actually, there exists general belief, or good will, that CZCE prices have developed or are developing a close relationship with CBOT prices based on 1) the fact that CZCE was established a decade ago with the help from CBOT so that many institutional features of the two markets are the same, and 2) some preliminary statistical calculation reveals the prices from the two markets have a strong association (CZCE Report, 2001).

Although China becomes more integrated to the world economy and its trade policy turns more liberalized after its WTO accession, the relationship between CZCE and CBOT has not shown a clear pattern yet. Although there are priori reasons to expect wheat futures prices in the two markets to move together more closely, there are also reasons to expect otherwise. Such reasons include the physical wheat trading volume between the two countries is still a small proportion compared to the domestic production and consumption levels, regulatory and institutional barriers still interfere with China’s market development, and futures traders involving in the two markets are not largely observed. Based on our data and analyses on wheat futures prices around the WTO accession, the cross-market effects are not yet evident in terms of cointegration in the mean level. It implies the long-run equilibrium relationship that binds the price movements in CZCE and CBOT are not existent. However, we still find transmission in the contract switching effect and volatility, depending on model specification, between the two markets. Although the linkage is not strong, it implies an asymmetric pattern. That is, CBOT has a stronger influence on CZCE than CZCE on CBOT, which implies CBOT’s leading role in the market interaction while CZCE is more like a follower. Such an interaction discloses the existence
of a weak connection between China’s and America’s wheat futures market on one hand, but on the other hand, the asymmetric property of the relationship indicates China’s wheat futures market is not strong enough to influence world market but is influenced by it.

The convergence problem we confront in estimation for periods not right before and after WTO accession may not be necessary due to bad data. It may correctly reflect the lack of comovements in the price behaviors in the two markets. Applying this to our analysis and expectation of interrelations between these two markets during those periods, it probably indicates that the even under the influence of WTO and globalization, integration of China’s wheat futures market to the world is still taking place much more slowly and can deviate more than expected.

V. Conclusion

After more than ten years of development, the CZCE has built up to the biggest commodity futures market in China and its wheat futures trading has important effects on wheat prices in China’s agricultural price system. This paper makes an effort to investigate the wheat futures price behavior in CZCE and more importantly the integration of CZCE to the world market, using CBOT as a representative. Previous studies on the market integration of China’s wheat futures market such as CZCE report (2001) focused the pairwise correlation analysis of prices and assumed constant price volatility. In this paper, we consider the cointegration relation and model price behavior of two wheat futures markets simultaneously based on time variant conditional variances, i.e. ARCH/GARCH.

Model fitting shows that both CZCE and CBOT price can be best modeled by ARCH(1)/GARCH(1,1) process. These results are consistent with the empirical studies of high frequency commodity prices (Myers, 1994; Poon and Granger, 2003). Bivariate analysis of CZCE
and CBOT prices shows the two series are not cointegrated. The existing cross-equation effects, i.e. the interrelations, between the two markets are significant but weak, and asymmetric under normal distribution. CBOT plays a leading role in the interactions and CZCE is more like a follower. This result reveals that the two prices evolve in a similar way and coincide to one another through the season, but there is not strong evidence for information flow from one market to the other. However, under t distribution, no significant evidence can be found for any interaction between the two markets. This means the relationship between the two markets has not shown a clear pattern.

The results indicate that the price in China’s wheat futures behaves in the similar way as the price in the represented world market, which is a good sign showing that the Chinese agricultural commodity market is performing in line with world markets. On the other hand, the short memory feature of CZCE compared to CBOT indicates that the CZCE is more volatile and chaotic, a sign showing that either the Chinese traders are less mature or the Chinese food market environment is less stable. The current one-way impact from CBOT to CZCE and the weak relation between the two markets indicate that China’s wheat market is not fully integrated with the world market yet.
Footnotes:

1. The low trading in 1999 was mostly affected by the regulatory change in CZCE, which was designed to discourage the mung bean trading. As a result, mung bean trading declined sharply and disappeared in the following years.

2. One US dollar equals about 8.3 Yuan.

3. The original data are in Yuan per metric ton for CZCE prices and in US dollar per bushel for CBOT prices. To make the two data series directly comparable in our study, we converted CBOT data into Yuan per metric ton using a constant factor, one metric ton equaling 36.74 bushels of wheat, and the exchange rate. The exchange rate stays constant in the study period.

4. For CBOT data, trading of the September 2000 contract started in July 2000. These early prices were not included until September 2001 when the September 2000 contract expired. CZCE data are arranged similarly. The old contract trading prices are chosen for this overlapping period because the old contracts are traded more actively than the new one during the period.

5. A normal distribution has both skewness and kurtosis at 0 as a benchmark.

6. At switching points, the estimated mean equation becomes $\Delta P_t = \hat{\alpha} + \hat{\delta} + \hat{\epsilon}_t$, where the right-hand-side of the equation represents the level of price changes when contract switches.

7. Although usually the joint t distribution is not well-defined, unlike its normal counterpart, it is defined in a certain way in s-plus GARCH module (S+ GARCH User’s Manual, pp107-108, Mathsoft, inc., March 2000). This definition is followed in our analysis.
Appendix. Derivation of own and cross market effects of conditional variances in a multivariate ARCH model (BEKK form)

By the definition of BEKK-ARCH(1), the conditional error variance equation can be specified as:

\[
\begin{pmatrix}
\sigma_{u}^2 \\
\sigma_{w}^2
\end{pmatrix} =
\begin{pmatrix}
\sigma_u \\
\sigma_w
\end{pmatrix} +
\begin{pmatrix}
A_{uu} & A_{uw} \\
A_{uw} & A_{ww}
\end{pmatrix}
\begin{pmatrix}
\sigma_{u}^2 \\
\sigma_{w}^2
\end{pmatrix} +
\begin{pmatrix}
u^2_t \\
v^2_t
\end{pmatrix}
\begin{pmatrix}
A_{uu} & A_{uw} \\
A_{uw} & A_{ww}
\end{pmatrix}
\]

To obtain the own and cross market effects from this specification, we take partial derivative of each dependent variable with respect to the respective explanatory variables to get the needed effects.

**Own market effects:**

\[
\frac{\partial \sigma_{u}^2}{\partial u^2_{t-1}} = A_{uu}^2, \quad \frac{\partial \sigma_{w}^2}{\partial v^2_{t-1}} = A_{ww}^2
\]

**Cross market effects:**

\[
\frac{\partial \sigma_{u}^2}{\partial v^2_{t-1}} = A_{uw}^2, \quad \frac{\partial \sigma_{w}^2}{\partial u^2_{t-1}} = A_{wu}^2
\]

**Other effects:**

\[
\frac{\partial \sigma_{u}^2}{\partial \sigma_{v_{t-1}v_{t-1}}} = 2A_{uw}A_{wu}, \quad \frac{\partial \sigma_{w}^2}{\partial \sigma_{v_{t-1}v_{t-1}}} = 2A_{ww}A_{ww}
\]

**Covariance effects:**

\[
\frac{\partial \sigma_{uv}}{\partial u^2_{t-1}} = A_{wu}A_{uw}, \quad \frac{\partial \sigma_{uv}}{\partial v^2_{t-1}} = A_{uw}A_{wu}, \quad \frac{\partial \sigma_{uv}}{\partial \sigma_{v_{t-1}v_{t-1}}} = A_{wu}A_{wu} + A_{uw}A_{ww}
\]
References


Figure 1. Annual Wheat Futures Trading in CZCE 1993-2003

Trading volume
(Million Contracts)

Trading value
(Billion Yuan)

Figure 2. CZCE and CBOT Wheat Futures Price for September Contract
Figure 3. Squared First Difference of CZCE and CBOT Wheat Futures Prices

CZCE September Contract

Unit: Yuan²/Ton²

CBOT September Contract

Unit: Yuan²/Ton²

Note: Since some squared first difference prices are way high compared to the rest, like those at switching points, we cut off most part of the spikes to fit them into the plot.
Table 1. Estimates of Selected Univariate ARCH/GARCH models

| Model         | $\varepsilon_t | \Omega_{t-1} \sim \text{normal}$ | $\varepsilon_t | \Omega_{t-1} \sim \text{student t}$ |
|---------------|------------------|------------------|
|               | CZCE - ARCH(1)   | CBOT - ARCH(1)   | CZCE - GARCH(1,1) | CBOT - ARCH(1) |
| $\beta_0$     | -0.77 (0.60)     | 0.54 (0.62)      | -0.22 (0.20)      | -0.13 (0.40)   |
| $\delta$      | 298.6* (0.76)    | -18.26 (70.27)   | 322.43* (18.08)   | -19.11 (37.80) |
| $\omega$      | 110.96* (0.89)   | 168.45* (2.41)   | 2.54* (1.11)      | 130.33* (12.93) |
| $\alpha_t$    | 0.05* (0.02)     | 0.10* (0.02)     | 0.04* (0.02)      | 0.12* (0.06)   |
| $\gamma_t$    | --               | --               | 0.94* (0.02)      | --             |
| AIC           | 4974.8           | 5449.5           | 4332.9            | 4359.7         |
| BIC           | 4992.7           | 5467.6           | 5215.0            | 5237.6         |

Note: 1. **"*" denotes significant at 5% level.
2. Standard errors are listed in the parentheses.
3. The estimated GARCH(1,1) model is defined as:
   $\Delta P_t = \beta_0 + \delta \varepsilon_t + \varepsilon_t | \Omega_{t-1} \sim N(0, h_t)$,
   where $h_t = \omega + \alpha_t \varepsilon_{t-1}^2 + \gamma_t h_{t-1}$ with $P_t$ denoting price at time $t$.
   The ARCH(1) is obtained when $\gamma_t$ is set to zero in the above specification.
Table 2. Estimates of Selected Multivariate ARCH/GARCH models

<table>
<thead>
<tr>
<th>Model</th>
<th>BEKK Modeling</th>
<th>CCC Modeling</th>
<th>DVEC Modeling</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ARCH(1) - N</td>
<td>ARCH(1) - t</td>
<td>GARCH(1,1) - N</td>
</tr>
<tr>
<td>$\mu^B$</td>
<td>0.009 (0.49)</td>
<td>-0.002 (0.48)</td>
<td>-0.16 (0.48)</td>
</tr>
<tr>
<td>$\mu^Z$</td>
<td>-0.97* (0.63)</td>
<td>-0.48* (0.31)</td>
<td>-0.15 (0.43)</td>
</tr>
<tr>
<td>$\Lambda_{BB}$</td>
<td>141.80* (11.49)</td>
<td>138.20* (6.76)</td>
<td>135.30* (4.69)</td>
</tr>
<tr>
<td>$\Lambda_{ZB}$</td>
<td>6.05 (56.13)</td>
<td>3.48 (13.75)</td>
<td>48.28* (1.96)</td>
</tr>
<tr>
<td>$\Lambda_{BB}$</td>
<td>3.21 (150.47)</td>
<td>1.74 (548.57)</td>
<td>3.98 (169.18)</td>
</tr>
<tr>
<td>$\Lambda_{ZZ}$</td>
<td>280.89* (5.66)</td>
<td>303.09* (22.73)</td>
<td>321.02 * (20.25)</td>
</tr>
<tr>
<td>$\omega_u$</td>
<td>11.34* (0.28)</td>
<td>11.40* (0.33)</td>
<td>2.13 * (1.64)</td>
</tr>
<tr>
<td>$\omega_v$</td>
<td>0.07 (0.64)</td>
<td>-0.17 (0.35)</td>
<td>-- --</td>
</tr>
<tr>
<td>$\omega_r$</td>
<td>10.83* (0.08)</td>
<td>6.72* (0.20)</td>
<td>5.64* (1.34)</td>
</tr>
<tr>
<td>$\Lambda_{uu}$</td>
<td>0.34* (0.05)</td>
<td>0.21* (0.06)</td>
<td>0.03* (0.009)</td>
</tr>
<tr>
<td>$\Lambda_{vv}$</td>
<td>-0.04 (0.14)</td>
<td>-0.01 (0.05)</td>
<td>-- --</td>
</tr>
<tr>
<td>$\Lambda_{uv}$</td>
<td>0.09 (0.10)</td>
<td>0.002 (0.08)</td>
<td>-- --</td>
</tr>
<tr>
<td>$\Lambda_{uv}$</td>
<td>0.20* (0.05)</td>
<td>0.46* (0.05)</td>
<td>0.22 (0.04)</td>
</tr>
<tr>
<td>$\Gamma_{uu}$</td>
<td>-- --</td>
<td>0.96 (0.02)</td>
<td>0.96* (0.02)</td>
</tr>
<tr>
<td>$\Gamma_{vv}$</td>
<td>-- --</td>
<td>-- --</td>
<td>-- --</td>
</tr>
<tr>
<td>$\Gamma_{uv}$</td>
<td>-- --</td>
<td>0.79* (0.04)</td>
<td>0.69* (0.03)</td>
</tr>
<tr>
<td>$\rho_{uv}$</td>
<td>-- --</td>
<td>-0.04 (0.05)</td>
<td>-0.02 (0.05)</td>
</tr>
<tr>
<td>AIC</td>
<td>9687.1</td>
<td>9398.4</td>
<td>9438.0</td>
</tr>
<tr>
<td>BIC</td>
<td>9744.8</td>
<td>9460.5</td>
<td>9438.0</td>
</tr>
</tbody>
</table>

Note: 1. "*" denotes significant at 95% level, and standard errors are listed in the parentheses.

2. The estimated ARCH(1) model in BEKK form is defined as:

$$\begin{align*}
\left( \Delta P_t^B \right) &= \left( \mu^B + \Lambda^B \right) + \left( \sigma^B \right)^2 + u_t, \\
\left( \Delta P_t^Z \right) &= \left( \mu^Z + \Lambda^Z \right) + \left( \sigma^Z \right)^2 + v_t,
\end{align*}$$

where $u_t$ and $v_t$ are innovations.

3. The GARCH(1,1) model in CCC form has the variance equation of the form:

$$\sigma_{i, t}^2 = \omega_i + \alpha_i \sigma_{i, t-1}^2 + \gamma_i \sigma_{j, t-1}^2, \quad i = u, v; \quad \sigma_{u, v} = \rho \sqrt{\sigma_{u, t}^2 \sigma_{v, t}^2}, \quad i, j = u, v, and i \neq j,$$

and the GARCH(1,1) model in DVEC form has a different variance equation:

$$\begin{align*}
\begin{pmatrix}
\sigma_{u, t}^2 \\
\sigma_{v, t}^2
\end{pmatrix} &= \begin{pmatrix}
\omega_u \\
\omega_v
\end{pmatrix} + \Lambda \begin{pmatrix}
\sigma_{u, t-1}^2 \\
\sigma_{v, t-1}^2
\end{pmatrix}, \\
\begin{pmatrix}
\alpha_u \\
\alpha_v
\end{pmatrix} &= \begin{pmatrix}
\omega_u \\
\omega_v
\end{pmatrix} + \Lambda \begin{pmatrix}
\sigma_{u, t-1}^2 \\
\sigma_{v, t-1}^2
\end{pmatrix},
\end{align*}$$

where $B$ denotes CBOT and $Z$ denotes CZCE.
Table 3. Within and Cross Market Effects of Bivariate BEKK-ARCH(1)

<table>
<thead>
<tr>
<th></th>
<th>$\sigma_{u,t}^2$</th>
<th>$\sigma_{uv,t}$</th>
<th>$\sigma_{v,t}^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_t</td>
<td>\Omega_{t-1} \sim normal$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$u_{t-1}^2$</td>
<td>0.1132</td>
<td>-0.0126</td>
<td>0.0014</td>
</tr>
<tr>
<td>$u_{t-1}v_{t-1}$</td>
<td>0.0579</td>
<td>0.0639</td>
<td>-0.0149</td>
</tr>
<tr>
<td>$v_{t-1}^2$</td>
<td>0.0074</td>
<td>0.0172</td>
<td>0.0398</td>
</tr>
<tr>
<td>$H_t</td>
<td>\Omega_{t-1} \sim student \ t$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$u_{t-1}^2$</td>
<td>0.0453</td>
<td>-0.0022</td>
<td>0.0001</td>
</tr>
<tr>
<td>$u_{t-1}v_{t-1}$</td>
<td>0.0007</td>
<td>0.0973</td>
<td>-0.0096</td>
</tr>
<tr>
<td>$v_{t-1}^2$</td>
<td>0.29E-5</td>
<td>0.0008</td>
<td>0.2091</td>
</tr>
</tbody>
</table>

Note: 1. The values reported values are calculated as in Appendix 1.
2. The estimated ARCH(1) model in BEKK form is defined as:

$$
\begin{align*}
\begin{pmatrix} \Delta P^u \\ \Delta P^v \end{pmatrix} & = \begin{pmatrix} \mu^u \\ \mu^v \end{pmatrix} + A \begin{pmatrix} SD^u \\ SD^v \end{pmatrix} + \begin{pmatrix} u_t \\ v_t \end{pmatrix},
\end{align*}
$$

where $\begin{pmatrix} u_t \\ v_t \end{pmatrix} \sim \begin{pmatrix} 0 \\ 0 \end{pmatrix}$, $\Omega_{t-1} = \begin{pmatrix} \sigma_{u,t}^2 & \sigma_{uv,t} \\ \sigma_{uv,t} & \sigma_{v,t}^2 \end{pmatrix}$.