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Price Discovery and Futures Spreads for U.S. and Chinese Rice Futures Market

Price Discovery and Futures Spreads for U.S. Chinese Rice Futures Market

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Agricultural Economics

by

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Abstract

Rice, the primary staple food for more than half the world's population, is the second world's most consumed food grain. In recent years, world rice price has increased and become more volatile especially in the period 2007-2010. Rice price volatility has a huge impact on Asian countries, especially countries in Southeast Asia where rice is a staple food for millions of households. Private market tools to manage price risk and discover price such as futures markets have been analyzed and assessed as possible solutions to coping with rice price volatility issue. Two primary functions of agricultural commodities futures markets are price discovery and price risk management. This thesis focused attention on the price discovery role of US and Chinese futures price spreads and their ability to impound information on supply and demand and storage costs. Our results show that the U.S. rice futures market responds to supply and demand information and incorporates storage costs. The U.S. rice futures market appears to be fulfilling its price discovery and storage role. Similarly, at least with respect to supply and demand information, the Chinese rice futures market spreads appear to follow the theory of storage and respond to supply and demand information.

Acknowledgments

I am sincerely thankful to my advisor, Dr. Andrew McKenzie for giving me the opportunity to do my Master's program with him. I am very grateful to work with such a professional, enthused and kind professor. Dr. McKenzie not only teaches me knowledge, he also teaches me a lot great things which will make me successful in the future career.

I also would like to thank my committee members for spending much time and energy on my study. Moreover, I appreciate their great recommendations and suggestions on my thesis.

I am very grateful to my family for supporting me forever and encouraging me to get through my hard time.

In the end, I would like to thank all the faculty members and students in the Department of Agricultural Economics and Agribusiness.

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I. Introduction

1. Rice and world rice market

Rice, the primary staple food for more than half the world's population, is the second most consumed food grain in the world, with 444 million metric tons globally consumed in 2011 (Childs and Hansen, 2013). Rice, as an ancient grain, originated in Asia and was domesticated as early as the fifth millennium, B.C.E. Nowadays, it has already been produced over vast areas of the world. Four major types of rice are produced worldwide: (1) Indica rice, which is mostly grown in tropical and subtropical regions, is the world's most traded variety, accounting for more than 75% of global trade. Cooked indicia are dry with separate grains. (2) Japonica rice. This is typically grown in regions with cooler climates and accounts for more than 10% of global trade. (3) Aromatic rice. This mostly includes jasmine from Thailand and basmati from India and Pakistan, and it accounts for 12% - 13% of global trade. This type of rice typically sells at a premium in world markets. (4) Glutinous rice. This mostly is grown in Southeast Asia and is consumed locally as well as in desserts and ceremonial dishes (USDA crop service).

Asia and Africa are the largest rice consuming regions in the world. Rice in these regions provides a vital source of calories (Liu et al., 2013). However, the global rice market is thin, concentered, and unstable with 95% of global rice production grown in developing countries (Food and Agriculture Organization of the United Nations, 2003). Nine out of the top ten rice producing countries are in Asia; Southeast Asia is the world's dominant rice export region (Childs and Hansen, 2013). Although rice is one of the top food grains consumed worldwide, most rice produced is consumed domestically and only 6-7% of global production is currently traded in international markets (Fig 1). In comparison 20% of global wheat production, 11% of

global corn production, and 35% of global soybean production is traded in international markets. Less global trading may lead to higher price volatility and larger annual price variations. Higher price volatility is associated with high levels of price risk for importing countries that may need to import a substantial amount of rice, especially if the major consuming/importing country has a crop shortfall (Childs and Baldwin, 2010).

Since the Second World War Asian countries have tended to turn to government intervention policies to curb rice price volatility and ensure food security for their populations. However, market based tools – such as futures and options markets – have played a major role in managing price risk associated with other raw commodities, especially in highly developed grain marketing systems such as are found in the USA. A primary goal of this thesis is to determine the economic efficiency and hence usefulness of the only two actively traded rice futures markets, which are based in the USA and China, as a price risk management tool. Specifically, this research will investigate the extent to which U.S. and Chinese rice futures markets play a price discovery role by incorporating supply and demand information and reflecting intertemporal storage costs. The ability of futures markets to successfully fulfill this price discovery role is essential if these markets are to be used by grain marketing systems as effective price risk management tools.

Before answering the question of whether U.S. and Chinese rice futures markets provide efficient price discovery it will be instructive to provide some historical perspective on world rice markets. The structure of the world rice market has been continually evolving and changing over the last 65 years. However, this period may be broken up into several distinct phases based upon trends and volatility in prices, production and the trade orientation of major exporters. The next section of the thesis provides a brief discussion of each of these phases.

World rice market during 1950-1964

During this period, the world rice market was an active market with high but stable prices. The major rice exporters were Thailand, Burma, Cambodia, and Vietnam which comprise all the nations of mainland Southeast Asia. Among these countries, Burma, Thailand, and Cambodia dominated world rice exports with a large share of their respective domestic production targeted for export market. Some 40% Burmese domestic rice production was exported from1950 to 1963; while 32% of Cambodian and 24% in Thai domestic production was exported over the same period. This high portion of domestic production destined for export was a means by which these countries could source foreign exchange earnings, and was an important source of government revenue (Dawe, 2002). For instance, more than 10% of Thailand government revenue came from taxes on rice exports during 1950-1965 (Siamwalla, 1975). Although the per capita rice production faced steep declines several times during this period, rice prices remained stable, because whenever Asian rice production was short, these three major rice exporters would supply exported rice to obtain revenue, which in turn ensured that severe price spikes were avoided. For example, despite the fact that Burmese per capita rice production fell by 15% in 1957, the country continued to export 43% of its total domestic production. Similarly Thailand, exported 40% of its domestic production during this period, although the Thai government was forced to enact quantitative restrictions to cope with a 33% fall of per capita production in 1957 (Dawe, 2002).

World rice market during 1965-1981

In contrast to the 1950-1964 period, rice prices during the 1965-1981 period were high and unstable. This period was referred to as "The Green Revolution" period as many modern

fertilizer-responsive rice varieties were developed and brought into crop production. Nevertheless, Asian per capita production and rice exports declined due to natural disasters and unstable political environment in the major rice exporting countries. By 1967 Burmese exports had declined to just 11% of domestic production due to restrictive government policies, and Burma effectively exited the world rice market in 1973 due to the world food crisis caused by a La Nina event. In addition, the Vietnamese government banned exports in 1965 until the late 1980s, and Cambodia and Thailand also decreased their rice exports over this period. The portion of rice export tax revenue to total Thai government revenue declined to 6% by 1967, and to 1% by 1971 (Siamwalla, 1975). Thai exports fell to 10% of domestic production from 1973 to 1975. These reductions in world rice exports from the major Asian exporting counties caused world rice price to jump 30% from 1965 to 1967.

World rice market during 1985-2000

During this period, the rice price in the world market was relatively stable, although there were a few notable price spikes. The previous world food crisis had led Thailand to steadily increase its domestic production, and Thai exports accounted for 40% of domestic production by the early 2000s. Vietnam also re-entered the world rice market during this period and approximately 20% of its domestic production was exported by late 1990s. The significant presence of Thailand and Vietnam in the world rice market contributed to a more stable price level. In addition, over this period more countries emerged as major rice exporters, such as India, China, Myanmar (formerly Burma) and Cambodia. This larger trading volume played an important role in stabilizing world rice prices.

World rice market after 2000

Post 2000 world rice markets became more and more active (Fig. 1). Global rice trade has nearly tripled since the mid-1980s (Childs and Baldwin, 2010). Especially for Southeast Asia which is the world's dominant rice export region, it is likely that exports will continue to increase over the next decade (Fig. 2). After 2000, agricultural commodity prices have increased and become more volatile, especially during the last five years (Alessandro and Vandone, 2013). Headey (2011) classified the drivers of world price volatility for rice into three main groups: (1) co- movement of agricultural commodities prices driven by oil prices, climate conditions, and financial speculation. High oil prices drive input prices higher for rice production, such as fertilizer, operation of rice production machinery, and irrigation. Climate change influences rice yield and the land suitable for production, which causes higher rice price volatility (Chen et al., 2012). (2) Closer price trend relationship between wheat and rice. This closer relationship may have been caused by a possible switching of importing countries from wheat to rice when the world price level of wheat was particularly high. In other words, rice has increasingly been seen as a possible substitute for wheat. This substitution effect could affect the demand for rice, and consequently affect the world rice price. Price shocks to wheat could increasingly spillover to the world rice market (3) Trade measures especially concerning export restrictions. In late September of 2007, the Vietnamese government was considered that over-selling rice exports to the global market would raise domestic food prices, so a partial ban on new sales was placed. Similarly, the Indian government placed a 20 days export ban in October, 2007, followed by a high minimum export price. These two countries rice export policies were associated with a surge in rice prices in 2007 – 2008, which has been referred to as the "world

rice crisis". This crisis has generated considerable interest among Asian countries as to the best way to stabilize world and domestic rice prices. We turn to this issue in the next section.

2. Rice price volatility and management

Given that rice is one of the most important crops for the poor in the world, and it supports 20% of global calories and 29% of calories for low-income countries (van Rheenen and van Tongeren, 2005) rice price levels and rice price stability are of prime concern to Asian and developing nations. In recent years, world rice price has increased and become more volatile especially in the period 2007-2010. The global rice price tripled in a matter of months in 2008 (Fig 3). Rice price volatility has a huge impact on Asian countries, especially countries in Southeast Asia where rice is a staple food for millions of households. For this region, large spikes in rice prices can lead to widespread hunger. As we have already alluded rice price volatility is driven by many factors. However, endogenous policy shocks – where governments ban rice exports and restrict private market trading – is perhaps the most important one. A relatively small portion of rice is traded in the global rice market, and the rice-producing counties have small surpluses to export compared to their consumption levels. Even the large rice-producing countries such as Bangladesh, China, India, and Indonesia are either deficient or at best marginally self-sufficient in domestic rice production (Jha et al., 2013). In this environment, rice-producing counties are likely to increase their domestic rice supplies through export restrictions or import tariff reductions in the face of another rice/food crisis. Asian importing countries, such as the Philippines, have attempted to introduce pricing policies to incentivize the production of domestic rice and reach the seemingly elusive goal of self-sufficiency. However, such policies are likely unsustainable and are very costly in transferring valuable resources from other sectors of the economy. Besides domestic polices to manage rice

price risk, Asian countries have also attempted to find other ways to manage rice price risk. Policies designed to increase trade liberalization in the region and to store a supply of rice reserves that could be released during price spikes have been advocated by various academics and world development agencies. Private market tools to manage price risk and discover price such as futures markets have also been analyzed and assessed as possible solutions to the rice price volatility issue. Certainly an actively traded Asian rice futures market would be an important tool to manage price volatility and discover price for Asian countries. In this context the price discovery role played by a potential Asian based rice futures market could help to make Asian and world rice prices more transparent, increase world rice trading volume, encourage storage and stabilize world and domestic rice prices. With this in mind we explore the economic price discovery role of two actively traded rice futures markets – the US CBOT market and the Chinese Zhengzhou market. Our question is – to what extent does these existing rice futures markets efficiently discover price and provide a storage mechanism to stabilize prices over a crop marketing year? If we can answer this question in the affirmative this gives greater credence to future policies designed to introduce a more widely based Asian rice futures market.

3. Futures market

Before analyzing the economic functionality of existing rice futures markets, we first discuss what a futures market is. A futures market, also known as a futures exchange, is a financial exchange in which different commodities are traded using standardized futures contracts. A commodity futures contract is an agreement which standardizes the quantity and quality of commodities bought or sold on a futures exchange. Trading can take place electronically or in a physical trading area. Futures traders may be separated into two categories: speculators and

hedgers. Speculators do not take any action in physical cash commodities markets, but only have interest in profiting from movements in futures prices. However, hedgers are interested in both cash commodities markets and futures markets. The hedgers trade futures to offset cash price risk caused by buying, selling and storing commodities in the physical cash market. Futures markets provide two important economic benefits: price discovery and price risk management. Futures price acts as a benchmark for physical cash market transactions and is used to quickly and efficiently inform traders of the fair market clearing price of physical cash grain. The price risk management role of futures markets is also of prime importance to the U.S. grain industry. Agribusiness firms likely use futures market to offset potential losses incurred from physical cash market trading by taking opposite position in futures to their actual current or anticipated cash positions. It is well understood by academics and industry participants alike that the major US grain futures markets (e.g. corn, soybeans and wheat) play a vital role in making the US grain marketing system the most efficient in the world. The economic contribution of the US rice futures markets has received less attention in academic literature and it is a less liquid (actively traded) contract than the other major grains – it is one of the goals of this thesis to further the economic understanding of the US rice futures market.

3.1 Chinese rice futures market

The Chinese cash rice market was strictly controlled by the government before the 1980s. During this period of strict control, Chinese urban residents could not buy rice from individuals or grain firms. They only could get rice from the official government supply chain for a fixed quantity per day. Rural residents grew their own rice instead of relying on government supply. They were not allowed to sell rice to any individuals expect to the government. Since the 1980s, the market has been gradually liberalized and the urban food rationing system was

abandoned after the 1990s (Liu et al., 2013). After abandoning the food rationing system, a movement was made towards a free market system. Urban residents could buy rice in the free market and rural residents could sell their rice to individuals or private grain firms besides the government (Sicular, 1995). Liberalization of Chinese grain and rice markets increased grain production, expanded grain trade, and made the market more competitive and integrated (Rozelle et al., 2000; Liu et al., 2013). The Zhengzhou wholesale grain market opened in October 12, 1990, and was the forerunner of Zhengzhou Commodity Exchange, which opened on May 28, 1993. The first early (meaning early season harvest) rice futures contract was traded on Zhengzhou Commodity Exchange on April 20, 2009. From 2009 to 2010, the early rice futures contract experienced large changes in trading volume and open interest (Fig 4). Both trading volume and open interest reached their peak in late 2010 and then both dropped dramatically. One reason given to explain the peak of trading volume and open interest is the large decrease in early rice production caused by bad weather in 2010. Another reason was the changes in early rice futures trading costs – 2010 trading costs were half of trading cost in 2009. However, in late 2010, the Zhengzhou Commodity Exchange raised trading costs and margin requirements on speculative positions making it less attractive to speculators. Immediately following these regulatory changes imposed by the exchange trading volume and open interest fell precipitously and almost "killed off" interest in the contract. However, since the beginning of 2012, early rice futures trading has gradually increased, and the Zhengzhou Commodity Exchange started a new early rice futures contract in July 2012. This new contract effectively replaced the old contract which ceased trading by May 2013. The new contract differs from the old contract in terms of contract size – the new contract is 20 tons while the old

contract was only 10 tons. This change in size specification was designed to increase commercial interest in the contract.

3.1.1 Chinese rice futures contract

The first early rice contract, which stared trading in April, 2009, was given the trading symbol ER. The contract specifications including standardized size, quantity and quality of rice are listed in Table 1. The minimum margin requirement of early rice futures is 5% of face value of a futures contract. Margin requirement varies based on the months that contracts trade. In the maturing month of the contract, the margin requirement is raised to 30% of face value of the futures contracts. In the month immediately before contract maturity, the margin requirements differ across trading days. Margin requirement of 8% of face value of futures contract is required in first 10 days. In second 10 days sequence margin requirement raises to 15% and to 25% in last 10 days of the month before contract maturity. In general trading during periods 2 or more months prior to contract maturity, margin requirements change based on the traders' position sizes and the amount of money in their trading accounts. 5% is the minimum margin requirement and 12% is the maximum margin requirement. The maximum volume of contracts that may be held by speculators is limited (Table 2) and depends upon the type of speculative firm, but there is no limit for hedgers. After early rice futures started trading, more and more companies entered the rice futures market. The average turnover is now 95,600 contracts/month, and the highest turnover was 3,526,200 contracts/month in 2010. With increased trading interest a new early rice contract, RI contract, was developed from and replaced the old ER early rice contract. This contract started to trade in July, 2012, and became the only early rice futures contract traded by May 2013.

3.1.2 Early rice

Early rice is a major crop of early harvested crops in China. It likely is used as a test crop to test polices to support crop production for Chinese government. Early rice is planted in 13 provinces including Hainan, Guangdong, Guangxi, Fujian, Jiangxi, Hunan, Hubei, Anhui, Zhejiang, Yunnan, Sichuang, and Guizhou. Among these provinces, Hunan, Hubei, Jiangxi, Guangdong, Anhui, Zhejiang, Guangxi, and Fujiang comprise the major production areas for early rice. Hunan, Guangxi, Jiangxi, and Guangdong comprise the four provinces with the largest early rice planting area, and about 80% of all early rice Chinese planting area. The production of early rice directly affects the production of later rice. Some studies indicated that the correlation coefficient between planting area of early to later rice was 0.93 during 1994 to 2005. Early rice has a short growth period of about 90-125 days and the environment is good for growth during this period. Thus, early rice typically has high yields and production. The harvest time of early rice is around late July. Early rice also is an important storage crop. The storage period of early rice is 3 years for almost all the major production areas. In this sense early rice futures would be a potentially useful tool to pay for hedgers storage costs.

It is difficult to say to what extent early rice futures are used for hedging purposes versus speculation in China. Anecdotal evidence – based upon conversations with rice traders and Singapore commodity exchanges – would suggest that the market has a large speculative component. The large fall in trading volume following increased margin requirement on speculative trades in 2010 would support this hypothesis. It is thus of great interest to empirically examine whether Chinese rice futures contracts play an effective price discovery role to aid rice storage decisions.

3.2 American rice futures market

3.2.1 U.S. rice production

The United States is a major exporter to the world rice market. The U.S. primarily exports rice to Mexico, Central America, Northeast Asia, the Caribbean, and the Middle East. U.S. produced rice accounts for 12-14% of the global rice market (Childs and Livezey, 2006). Almost all U.S. rice is produced in four regions which include six states: Arkansas, California, Louisiana, Mississippi, Missouri, and Texas (Salassi et al., 2013). In 2013, 189,886,000 cwt of rice was harvested from 2,468,000 acres in U.S. Arkansas is the major rice producing state in the U. S. All rice is produced in irrigated fields, but specific types of rice differ across states. Types of rice are referred to by length of grain such as long, medium, and short. Long-grain rice varieties typically are dry and separate after cooking. Long-grain rice is planted in 6 rice-producing states. Arkansas is the major long-grain rice producing state. In 2013, Arkansas long-grain rice planting area accounted for 53.8% of all U.S. rice planting area and the harvest amount was 54.45% of total U.S. long-grain rice. Whereas, only 0.34% of long-grain rice was planted in California, which accounted for 0.26% of total long-grain rice production. Medium-grain rice is typically planted in 5 of 6 rice producing states with the exception being Mississippi. Among these states, California is the major planting and producing state was and accounted for 77.86% of U.S. medium rice planting area and 80.52% of production in 2013. Missouri and Texas only had a tiny medium-grain rice planting area and a very small portion of production in 2013. Arkansas and California were the only states to plant short-grain rice in 2013, with California being the major production state.

3.2.2 U.S. rice futures

Agricultural commodity futures markets play a price discovery and risk management role for US grain marketing system. The U.S. rough rice futures contract has about a 30 year trading history. It first traded at the Mid-America Commodity Exchange and then the Chicago Rice and Cotton Exchange which were the affiliates of the Chicago Board of Trade (CBOT). In 1994, rough rice futures and options on futures were directly traded at the CBOT. CBOT specifies the rough rice futures contract in terms of standardized measure of quantity and quality of rough rice (Table. 3)

The contact specifications satisfy the hedging requirements of industry participants. The size of the contract satisfies the hedgers' need and also matches typical modes of transportation. Delivery locations of rough rice futures contract are situated in the eastern Arkansas, which is the major cash production area of long-grain rice. It is likely that the CBOT specified the contract on long-grain rough rice, rather than say milled rice, because rough rice is storable over the post-harvest marketing year. Once rice is milled it tends to be shipped for consumption fairly quickly. One of the most important functions of grain futures markets is to provide pricing signals for storage decisions. One of the main goals of this thesis is to determine how efficient the U.S. rice futures market is in incorporating supply and demand and storage cost information and providing associated pricing signals.

II. Methodology

Price discovery is a major function of futures market. Futures prices can quickly and efficiently inform market participants of fair market prices by incorporating market information such about production, storage, exports and import, etc. (McKenzie, 2012). There two key ways in which futures markets provide price discovery. First, it is widely recognized in the literature that commodity futures markets provide unbiased forward looking price forecasts for specific delivery locations and for a series of delivery times – up to three years ahead. Using this metric one would expect futures prices for different delivery periods and futures spreads – the difference between two futures prices for different delivery periods – to accurately reflect supply and demand information. In this context the U.S. rice futures market is efficient based on the research conducted by McKenzie et al. (McKenzie et al., 2002).

Secondly, futures markets provide price discovery in terms of futures price. In this context, and in line with the theory of storage, the futures market is deemed to provide efficient price discovery if the futures spread accurately reflects the storage costs associated with holding a commodity from one period to the next. The theory of storage describes the futures spread in terms of the interest forgone in storing a commodity, warehousing costs, and convenience yield on inventory (Fama and French, 1987). Prior research has shown that for US soybean markets futures price spreads reflect storage costs over several months following harvest (Zulauf, Zhou and Roberts, 2006). Some research has also argued that futures price spreads reflect convenience yields, although this remains a controversial issue. From a practical standpoint, this form of price discovery is essential in providing US grain elevators with signals of when and how long to hedge stored grain – referred to in the industry as basis trading. Grain industry regards carry spreads (where futures contracts for deferred delivery periods trade at higher

levels than nearby futures contracts – reflecting storage costs) as the futures markets way of paying elevators to store grain. If the futures market is unable to efficiently reflect storage costs this compromises the whole grain marketing system.

With this in mind this thesis will analyze both metrics of price discovery – the ability of futures spreads – observed in Chinese and U.S. rice futures markets to reflect supply and demand information along with storage costs. Following Zulauf, Zhou, and Roberts (2005) we analyze futures spread behavior following the release of stocks-to-use ratio information contained in World Agricultural Supply and Demand (WASDE) reports. Unlike Zulauf, Zhou, and Roberts, who analyzed soybean futures spread movements with respect to new crop stocks-to-use ratios on an annual basis, we analyze Chinese and US rice futures spreads behavior with respect to monthly releases of old crop stocks-to-use ratios. So in this sense we extend the work of Zulauf, Zhou and Roberts by increasing the frequency and quantity of our observations and by analyzing rice futures – a market whose behavior has received relatively little attention compared with the large volume grain market contracts such as corn and soybeans. To account for contemporaneous correlation across simultaneously traded futures contracts prices observed on a monthly basis we use a generalized least squares procedure as outlined in Karali and Thurman (2009). Karali and Thurman used this approach to investigate the reaction of lumber futures returns to monthly housing starts announcements. Their analysis focused on individual futures contract behavior rather than spread behavior.

1. Data resource

1.1 Futures spread

The prices of U.S. rough rice futures were collected from the White Commercial Corporation. All the prices of U.S. rough rice futures contracts for post-harvest delivery periods for each marketing year from September 1995 to March 2014 were used to calculate historical futures spreads. The futures spreads were calculated as the difference between successive nearby contracts such as November-January spread, January-March spread, March-May spread, and May-July spread. These spreads represent two-month storage periods throughout the US rice marketing season which begins each August through September of the following year. In this thesis future spreads were only analyzed for the storage part of the marketing year (e.g. September through May of the following year). All US rice futures spreads are measured in cents per CWT (hundredweight). Futures spreads ration the supply of a crop by creating incentives to carry grain if there is an ample supply of it, and by penalizing grain storage if the crop is short. When spreads are at a carry (distant contract prices higher than nearby) the market is telling you to hold the grain until later, and when spreads are inverted (distant contract prices lower than nearby) the market is telling you to sell now (Fig 5). Futures Prices typically tend to follow a Carry stair-step pattern after harvest under normal supply and demand conditions (Fig 6).

The prices of Chinese early rice futures contracts were collected from 2009 to 2014 from a web-based database provided by Zhengzhou Commodity Exchange. The Chinese contract delivery months are the same as the US contracts, but the marketing season differs as harvest time for early rice is around July in China. Two kinds of early rice futures contract prices were collected. One was the ER early rice futures contract which stopped trading in May 2013. The

last ER contract matured in May 2013. The other was the RI early rice futures contract which started trading in January 2013. The first RI contract matured in July 2013. For our empirical analysis these two kinds of early rice contracts were deemed to be equivalent and price data from both contracts were merged creating a continuous data set without any time gaps. The only major difference between these two types of contracts was with respect to the contract size (contract size of ER is 10 Tons and RI is 20 Tons). Thus, the prices of two kinds of contracts were combined to form complete set of data in which first part data was ER contract and last part data was RI contract. All Chinese rice futures spreads are measured in terms of Yuan per ton.

Four different categories of spreads are calculated using the early rice futures prices: September-November, November-January, January-March, and March-May.

In both the US and China, all futures contract spreads overlap throughout the respective marketing years/season because of different delivery periods (Fig 7).

1.2 Stock/use ratio

Stock/use ratio is a good tool to understand the big picture of supply and demand and it is widely used by the grain industry to make hedging and storage decisions. It is the ratio of projected ending stock of a crop and projected total use of a crop for a marketing year/season. The formula used to calculate stock/use ratio is as follows:

$$\frac{Projected\ ending\ stocks}{Projected\ total\ use\ for\ that\ season} \times 100\%$$

Historical data of projected ending stocks and projected total use was collected from World Agricultural Supply and Demand Estimates report (WASDE) published by U.S. Department of

Agriculture (USDA). Around the 12th day of each month the WASDE report provides supply and utilization of different crops such as rice, soybeans, wheat, corn, etc. for the US and global markets. The Interagency Commodity Estimates Committee (ICEC) compile the report by collecting reported data from National Agricultural Statistics Service (), Foreign Agricultural Service (FAS), Farm Services Agency (FSA), Farm Services Agency (FSA), and Economic Research Service (ERS). NASS provides estimates of U.S. crop production, stocks and monthly farm prices. FAS supports commodity information and market developments in foreign countries. FSA provides information related to farm programs and their influence on U.S. production and from Economic Research Service (ERS) which provides basic economic analysis of world and U.S. supply and demand conditions, including country and regional analysis (Aaronson and Childs, 2000). Based on all the available information, ICEC gives publishes short-term forecasts of stocks and use of various crops over a given marketing year. The data used in this thesis is projected stocks and use for different kinds of U.S. rice, including total rough rice, milled rice, rough long grain rice and rough medium grain rice, Given the timeline of the US harvest period and marketing season, WASDE stocks to use ratio projections for September through April are actually projections of the most recent US rice harvest production, carryover stocks, and expected use over the forthcoming year. So for example, for the 2013/14 crop year, our March 2014 observation would be a forecast of the 2013 harvest-time production, the beginning stocks as of August 2013, and the projected ending stock for August 2014 – based upon the residual of total usage over the 2013/14 marketing year less 2013 production and beginning stocks. We would consider that this stock- to-use information is most pertinent to the 4 post-harvest "storage" futures spreads analyzed in this thesis. Each May the WASDE report contains the first projection of the forthcoming year's harvest production.

Chinese rice stocks and use projected data is also used, and both US and Chinese data is collected from WASDE reports published by USDA from September 1995 to March 2014.

The theory of storage would suggest that there should be a strong economic relationship between stock/use ratio and futures spreads. In general, the higher the ratio, the wider carry spreads will be following harvest, and vice versa. Very low ratios are associated with inverted spreads. This phenomenon has been observed in the U.S. crops futures markets such as soybean futures market, corn futures market, and rice futures market, as well as in Chinese rice futures market (Fig 8, 9, 10, 11).

2. Data

2.1 Models

In this thesis the extent to which movements in US and Chinese rice futures price spreads can be explained by forward looking supply and demand information for a marketing year , was analyzed in a regression framework:

$$Futures\ spread = \alpha + \beta\ stocks/use\ \ ratio + \varepsilon \quad (1)$$

The independent variable, stocks/use ratio, was calculated using the formula mentioned before. The dependent variable, futures spread, was calculated by the futures price of one delivery period contract minus the price of next delivery period contract. These two different delivery period contracts were traded simultaneously. The α term represents a constant and ε is assumed to be a normally distributed uncorrelated error term.

US and Chinese rice futures contracts settlement prices were collected 3 days after each monthly WASDE report was published (some prices were collected beyond the 3 days after WASDE report was published because on the third day the exchange was closed for holidays or

weekend.). It was assumed that 3 days would be enough time for the futures market to absorb and adjust to release of new WASDE information. Although futures prices tend to react immediately to the release of report information institutional idiosyncrasies of the futures markets – such as daily limit price moves – may prevent a full price adjustment in the immediate aftermath of a report release date.

In addition to stock to use ratios, and based on the theory of storage, the difference between futures price and spot price or between futures prices for different delivery periods can be explained by the cost of storing a commodity over time. Much prior research had empirically tested this concept e.g. Brennan (Brennan, 1958), Scheinkman and Schechtman (1983), Thurman (Thurman, 1988), Williams and Wright (2005). So in order to consider the impact of both variation in stock to use ratios and storage costs on futures price spreads the following regression model was specified:

$$Futures\ spread = \alpha + \beta 1\ stocks/use + \beta 2\ storage\ cost + \varepsilon \quad (2)$$

where again, the α term represents a constant and ε is assumed to be a normally distributed uncorrelated error term. The two-month storage cost was calculated by the formula shown as follows:

$$Storage\ cost = current\ Interest\ rate\ \times Future\ price\ of\ nearby\ maturity\ contract \times (60\ /360\ ) \times 100\%$$

where 60 is measures the number of trading and storage days between two rice futures contracts delivery periods – the futures spread, and 360 represents the number of banking days in a year. Historical daily St. Louis Federal Reserve Bank prime short term interest rates represent the

current US interest rate. Thus US storage costs are measured in cents per CWT (hundredweight).

The Chinese interest rate is taken from the People's Bank of China, and hence Chinese storage costs are measured in Yuan per ton.

Given that the futures contracts trade simultaneously at any point in time, we observe up to 4 futures spreads observations. These futures spread observations are likely correlated and when modeled in a regression framework the error term, ε, is likely non-normal – not iid. To account for potential contemporaneous autocorrelation across and hetreroskedasticity – induced by delivery specific futures contracts – in the error term the empirical analysis pursued in this thesis follows a generalized least squares (GLS) method developed by Karali and Thurman (2009) to transform the futures spreads, stocks to use ratios and storage costs data. One statistical advantage of measuring futures behavior in terms of spreads – the dependent variable specified in models 1 and 2 – is that the data is stationary and we do not have to account for unit roots. In effect using spread data is akin to differencing the futures series.

2.2 Data organization

With the data issues in mind and to implement the GLS procedure all of the futures spreads were divided to four categories based on the number of futures spreads traded simultaneously at any point in time during our data series: For example, with respect to US rice futures, observations for September, October and November include 4 simultaneously traded spreads: the November-January spread, January-March spread, March-May spread, and May-July spread. Similarly, observations for December and January include 3 simultaneously traded spreads: the January-March spread, March-May spread, and May-July spread. While

observations for March include 2 simultaneously traded spreads: the March-May spread and May-July spread. Finally, observations for April and May include only 1 spread: the May-July spread. The various spread groupings are presented in table 4, with Y_i denoting group in terms of number of simultaneously traded spread contracts *i*, and y_i denoting the different spreads within a group with *i* representing the sequence of spreads from nearby (1) to next nearby (2) and so on. By grouping simultaneously traded spreads in this manner we are able to account for correlation structure and hetreroskedasticity in our model variance-covariance matrix. As Karali and Thurman note "simply pooling the time series and ignoring contemporaneous correlation would falsely imply that each observation provided an independent observation…" (Page 434)

Thus for U.S. rough rice futures market, we have 219 monthly observations for the group containing 4 simultaneously traded spreads: 114 observations for the group containing 3 simultaneously traded spreads; 76 observations for the group containing 2 simultaneously traded spreads; and 36 observations for the group containing just 1 traded spread. With respect to Chinese early rice futures market, we have 60 monthly observations for the group containing 4 simultaneously traded spreads; 24 observations for the group containing 3 simultaneously traded spreads; 20 observations for the group containing 2 simultaneously traded spreads; and 10 observations for the group with just 1 traded spread. In sum, we have 445 total observations collected from U.S. rough rice futures market, and a total of 114 observations collected from Chinese early rice futures market. Following the approach described in Karali and Thurman developed (2009) pages 433 - 436:

$$Y1 = [y_{1,t_1^1} \quad y_{1,t_2^1} \quad \cdots \quad y_{1,t_{n_1}^1}]$$

$$Y2 = [y_{1,t_1^2} \quad y_{1,t_2^2} \quad \cdots \quad y_{1,t_{n_2}^2}, \quad y_{2,t_1^2} \quad y_{2,t_2^2} \quad \cdots \quad y_{2,t_{n_2}^2}]$$

$$Y3 = \left[y_{1,t_1^3} \quad y_{1,t_2^3} \cdots y_{1,t_{n_2}^3}, y_{2,t_1^3} \quad y_{2,t_2^3} \cdots y_{2,t_{n_2}^3}, y_{3,t_1^3} \quad y_{3,t_2^3} \cdots y_{3,t_{n_3}^3} \right]$$

$Y4$

$$= \left[y_{1,t_1^4} \quad y_{1,t_2^4} \cdots y_{1,t_{n_2}^4}, y_{2,t_1^4} \quad y_{2,t_2^4} \cdots y_{2,t_{n_2}^4}, y_{3,t_1^4} \quad y_{3,t_2^4} \cdots y_{3,t_{n_3}^4}, y_{4,t_1^4} \ \ y_{4,t_2^4} \cdots y_{4,t_{n_4}^4} \right]$$

where y_1, y_2, y_3, and y_4 refer to the spread values contained in each spread group, with y_1 denoting the nearby contract, y_2 denotes the next nearest to delivery contract and so on. The term t_j^k refers to jth day in k-spread group (Table 3). For instance, Y4 is a matrix comprising all the spread values in the group of 4 simultaneously traded spreads. y_{1,t_1^4} represents the spread value for the trading day of the nearby spread observed in the first calendar month of the 4-simultaneosuly traded spread group. So for example, for this would represent the September observation of the November-January spread.

All four vectors above are then stacked to form a new vector Y:

$$Y = [Y1 \quad Y2 \quad Y3 \quad Y4]$$

The independent variables, stock/use ratios and storage costs, were also organized in the same way to match the periodicity of the futures spreads.

Then ordinary least squares (OLS) regressions were run for our two models using the data organization described above. The residuals from OLS regressions were then arranged in the following submatricies using the same notation as above:

$$\varepsilon 1 = [e_{1,t_1^1} \quad e_{1,t_2^1} \quad \cdots \quad e_{1,t_{n_1}^1}]$$

$$\varepsilon 2 = \begin{bmatrix} e_{1,t_1^2} & e_{1,t_2^2} & \cdots & e_{1,t_{n_2}^2} \\ e_{2,t_1^2} & e_{2,t_2^2} & \cdots & e_{2,t_{n_2}^2} \end{bmatrix}$$

$$\varepsilon 3 = \begin{bmatrix} e_{1,t_1^3} & e_{1,t_2^3} & \cdots & e_{1,t_{n_3}^3} \\ e_{2,t_1^3} & e_{2,t_2^3} & \cdots & e_{2,t_{n_3}^3} \\ e_{3,t_1^3} & e_{3,t_2^3} & \cdots & e_{3,t_{n_3}^3} \end{bmatrix}$$

$$\varepsilon 4 = \begin{bmatrix} e_{1,t_1^4} & e_{1,t_2^4} & \cdots & e_{1,t_{n_4}^4} \\ e_{2,t_1^4} & e_{2,t_2^4} & \cdots & e_{2,t_{n_4}^4} \\ e_{3,t_1^4} & e_{3,t_2^4} & \cdots & e_{3,t_{n_4}^4} \\ e_{4,t_1^4} & e_{4,t_2^4} & \cdots & e_{4,t_{n_4}^4} \end{bmatrix}$$

From the residual submatricies we are able to calculate a 4 X 4 variance-covariance matrix associated with observations across the 4 different contract spreads. This is achieved by using the following formulas to calculate each of the variance and covariance elements of the variance-covariance matrix:

$$\hat{\sigma}_1^2 = \frac{\sum_{k=1}^{4} \sum_{j=1}^{n_k} \left(e_{1\, t_j^k} \right)^2}{n_1 + n_2 + n_3 + n_4} \qquad \hat{\sigma}_2^2 = \frac{\sum_{k=2}^{4} \sum_{j=1}^{n_k} \left(e_{2\, t_j^k} \right)^2}{n_2 + n_3 + n_4}$$

$$\hat{\sigma}_3^2 = \frac{\sum_{k=3}^{4} \sum_{j=1}^{n_k} \left(e_{3\, t_j^k} \right)^2}{n_3 + n_4} \qquad \hat{\sigma}_4^2 = \frac{\sum_{j=1}^{n_k} \left(e_{4\, t_j^k} \right)^2}{n_4}$$

$$\hat{\sigma}_{12} = \frac{\sum_{j=1}^{n_2} e_{1\, t_j^2} e_{2\, t_j^2} + \sum_{j=1}^{n_3} e_{1\, t_j^3} e_{2\, t_j^3} + \sum_{j=1}^{n_4} e_{1\, t_j^4} e_{2\, t_j^4}}{n_2 + n_3 + n_4}$$

$$\hat{\sigma}_{13} = \frac{\sum_{j=1}^{n_2} e_{1\, t_j^3} e_{3\, t_j^3} + \sum_{j=1}^{n_4} e_{1\, t_j^4} e_{3\, t_j^4}}{n_3 + n_4}$$

$$\hat{\sigma}_{14} = \frac{\sum_{j=1}^{n_4} e_{1\, t_j^4} e_{1\, t_j^4}}{n_4}$$

$$\hat{\sigma}_{23} = \frac{\sum_{j=1}^{n_3} e_{2\,t_j^3} e_{3\,t_j^3} + \sum_{j=1}^{n_4} e_{2\,t_j^4} e_{3\,t_j^4}}{n_3 + n_4}$$

$$\hat{\sigma}_{24} = \frac{\sum_{j=1}^{n_4} e_{2\,t_j^4} e_{4\,t_j^4}}{n_4}$$

$$\hat{\sigma}_{34} = \frac{\sum_{j=1}^{n_4} e_{3\,t_j^4} e_{4\,t_j^4}}{n_4}$$

Thus the 4 X 4 variance-covariance matrix, labelled $\sum$, takes the form:

$$\sum = \begin{bmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} & \hat{\sigma}_{13} & \hat{\sigma}_{14} \\ \hat{\sigma}_{21} & \hat{\sigma}_2^2 & \hat{\sigma}_{23} & \hat{\sigma}_{24} \\ \hat{\sigma}_{31} & \hat{\sigma}_{32} & \hat{\sigma}_3^2 & \hat{\sigma}_{34} \\ \hat{\sigma}_{41} & \hat{\sigma}_{42} & \hat{\sigma}_{43} & \hat{\sigma}_4^2 \end{bmatrix}$$

Then we use the Cholesky decomposition of $\sum$ to apply a Generalized Least Squares (GLS) transformation to the data to eliminate contemporaneous correlation among the residuals and adjust the observations to be homoscedastic. The Cholesky factors C_i are calculated by using the following formulas.

$$C_1 C_1^{'} = \hat{\sigma}_1^2$$

$$C_2 C_2^{'} = \begin{bmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} \\ \hat{\sigma}_{21} & \hat{\sigma}_2^2 \end{bmatrix}$$

$$C_3 C_3^{'} = \begin{bmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} & \hat{\sigma}_{13} \\ \hat{\sigma}_{21} & \hat{\sigma}_2^2 & \hat{\sigma}_{23} \\ \hat{\sigma}_{31} & \hat{\sigma}_{32} & \hat{\sigma}_3^2 \end{bmatrix}$$

$$C_4 C_4^{'} = \begin{bmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} & \hat{\sigma}_{13} & \hat{\sigma}_{14} \\ \hat{\sigma}_{21} & \hat{\sigma}_2^2 & \hat{\sigma}_{23} & \hat{\sigma}_{24} \\ \hat{\sigma}_{31} & \hat{\sigma}_{32} & \hat{\sigma}_3^2 & \hat{\sigma}_{34} \\ \hat{\sigma}_{41} & \hat{\sigma}_{42} & \hat{\sigma}_{43} & \hat{\sigma}_4^2 \end{bmatrix}$$

where the value of $\hat{\sigma}_{kj}$ is equal to $\hat{\sigma}_{jk}$.

Then new independent variables matrices data and new dependent variable matrix data are then created by pre-multiplying the original variable submatricies by the assoicated inverse Cholesky factors. For example:

$$Y4^{*} = [(C_4^{'})^{-1} Y4^{'}]^{'} = \left((C_4^{'})^{-1} \begin{bmatrix} y_{1,t_1^4} & y_{1,t_2^4} & \cdots & y_{1,t_{n_4}^4} \\ y_{2,t_1^4} & y_{2,t_2^4} & \cdots & y_{2,t_{n_4}^4} \\ y_{3,t_1^4} & y_{3,t_2^4} & \cdots & y_{3,t_{n_4}^4} \\ y_{4,t_1^4} & y_{4,t_2^4} & \cdots & y_{4,t_{n_4}^4} \end{bmatrix} \right)^{'}$$

This procedure completes the GLS transformation of the data following Karali and Thurman (2009). However, diagnostic test results (Durbin Watson tests) presented in column 7 of table 6 indicate that our GLS estimations of models 1 and 2 suffer from serial correlation. Note that the Karali and Thurman procedure de-correlates the data only with respect to contemporaneous correlation across futures contract spreads. Therefore to account for first order serial correlation we re-estimate models 1 and 2 using AR(1) model adjustment estimated by Cochrane-Orcutt method in SHAZAM on the GLS transformed data. The regression models results for OLS and GLS estimations are presented in table 6, while the GLS estimation results are compared to GLS-AR (1) estimation results in table 6. Given the presence of heteroskedasticity, and contemporaneous and serial correlation – which has implications in terms of biased parameter estimates, parameter estimates standard errors and associated parameter tests of statistical inference– in the data we regard the GLS-AR(1) results as the most reliable.

III. Results

1. OLS and GLS Regression results

Table 5 presents regression results for OLS and GLS estimation of models 1 and 2. A priori and based upon theory of storage, prior literature, and industry observation we would expect that both storage costs and stocks-to-use ratios would be positively related to futures spreads. In industry terminology, higher stocks/use ratio are associated with and are said to cause the wider carry futures spreads following harvest-time.

For model 1, which explains movements in futures spreads in terms of stocks-to-use ratios alone, our GLS results indicate that a significantly positive relationship exists on average (β = 0.83) between Chinese stocks-to-use ratios and Chinese futures spreads. In contrast the OLS results for this case are insignificant. R^2 value is small which is 0.1018 shows that the Chinese stocks-to-use ratio although having a significant impact on futures spreads are not able to explain much of the overall variance in Chinese futures spreads movements.

Our model 1 results with respect to US total rough rice, US milled rice, US long grain rough rice, and US medium grain rough rice in general show a statistically positive relationship exists between US long grain rough rice futures spreads and stocks-to-use ratios for each category of rice. The only exception is the OLS result with respect to medium grain rice, where the stocks-to-use ratio coefficient is small and insignificant. So, our US and Chinese model 1 results are consistent with theory of storage and prior literature. For example Zulauf, Zhou and Roberts find a significantly positive relationship between soybean stocks-to-use ratios and soybean futures spreads. However, again R^2 values are small – only 0.00004 for medium grain, and 0.012 for long grain – which shows that the US stocks-to-use ratios irrespective of grain type

while having a significant impact on average on futures spreads explain a negligible portion of variance in US futures spreads movements. This result may be an artifact of using monthly stocks-to-use ratio data based upon old crop projections over the September – April period that exhibit little variation over time.

Our OLS and GLS model 2 results, which capture the additional effect of storage costs on futures spreads are presented in table 5. Chinese storage costs do not add any additional explanatory power to describe Chinese futures spreads movements (the coefficient on storage costs is insignificant), but stocks-to-use ratio in model 2 has similar power and size as in model 1.

Our GLS US results show that both stocks-to-use ratios and storage costs have a positive and statistically significant impact on US long grain rough rice futures spreads. All coefficients for stocks-to-use and storage costs are positive and significant irrespective of rice type. However, R^2 values across all of our model 2 specifications are again very small. This result may also be attributed to the monthly storage cost data which has little month to month variability over the September – April period. It should be noted that Yang and McKenzie (2014) using annual data from 2000 – 2014 found that US stocks-to-use ratios for total rough rice and US storage costs could explain 34% of variation in November-January US long grain rough rice futures spreads. Using this annual model the estimated stocks-to-use coefficient was 1 and the estimated storage costs coefficient was 0.82. These results are roughly in line with our GLS and GLS-AR(1) parameter estimates from model 2 presented in tables 4 and 5. The use of annual data allows for more variation in futures spreads, stocks-to-use ratios and storage costs and avoids serial correlation and heteroskedasticity issues. However, a negative trade-off of using annual data is that few observations are available – reducing parameter estimate precision. With this in mind

we turn to our GLS-AR(1) results for models 1 and 2, which we believe provide the most reliable and precise parameter estimates.

3. GLS-AR(1) Regression results

Table 6 presents both GLS (left hand side of table) and GLS-AR(1) (right hand side of table) results for comparison purposes. With respect to model 1 the GLS-AR(1) results are similar to the GLS results with stocks-to-use ratios having a significant and positive impact on futures spreads for Chinese and all US rice types. However, for US rice types this effect is somewhat smaller in magnitude after accounting for the AR(1) process in the residuals. In sum, our model 1 results clearly show that higher stocks-to-use ratios lead to wider or larger carry futures spreads – whereby the relative pricing difference between distant and nearby futures contracts increases. This is consistent with theory of storage, prior literature and industry observations. As relatively more supply of rice is grown, cash spot prices and nearby futures prices fall relative to distant futures prices – futures spreads widen – providing incentives to store. It appears that Chinese and US rice futures prices are fulfilling their important storage information role in their respective marketing systems.

Our GLS and GLS-AR(1) model 2 results are shown in the lower half of table 6. Notably for China our GLS-AR(1) results confirm our earlier finding that storage costs do not affect Chinese futures spreads. This is perhaps not a surprising finding as our data on Chinese rice storage costs has little variability over the sample period and the interest rate data used to measure storage costs may not accurately reflect the borrowing rate faced by rice storage firms.

For US rice types our GLS and GLS-AR(1) results are very similar with parameter estimates almost identical in terms of size and significance – both stocks-to-use ratios and

storage costs have a significantly positive impact on US rough rice futures spreads. Again, our results are consistent with the theory of storage. Higher storage costs – measured as the opportunity cost of holding rice instead of immediately selling it – are associated with relatively wider futures carry spreads. In other words, the magnitude of the price difference between distant and nearby futures prices must increase – distant contracts trade at successively higher relative price levels – to compensate or pay for the higher storage costs and induce firms to store.

Interestingly, although the underlying cash market upon which US rice futures contracts are specified is long grain rough rice futures stocks-to-use measures for all rice types, total rough rice (long and medium grains combined), milled rice and medium grain rice alone, all have a significantly positive relationship with US rice futures spreads. This finding is not unexpected with respect to total rough rice and milled rice stocks-to-use ratios. Typically, the supply of long grain rough rice is much larger than the supply of medium grain rough rice in most crop years and so total rough rice stocks are highly correlated to long grain rough rice stocks. Similarly, although milling yields vary from year to year, the overall stock levels of total rough rice and milled rice are highly correlated. Somewhat more surprising is the finding that medium grain stocks-to-use ratios have on average a significantly positive – although smaller in magnitude – impact on long grain rough rice futures spreads. Certainly, medium and long grain cash prices are not highly correlated over time. There is only 29.4% negative correlation between long and medium grain cash prices (data source from rough rice: Average price received by farmers by month and market year by class published by USDA)

IV. Conclusion

Two primary functions of agricultural commodities futures markets are price discovery and price risk management. This thesis has focused attention on the price discovery role of US and Chinese futures price spreads and their ability to impound information on supply and demand and storage costs. Previous research has shown that USDA WASDE reports are important sources for agricultural commodities supply and demand (McKenzie, 2011). Much previous research has analyzed the efficiency of US commodity futures markets to quickly incorporate information contained in USDA reports and provide price discovery to corn and soybean markets (e.g. Good and Irwin, 2005; Mckenzie, 2008). However, this body of research has analyzed the reaction of futures prices to the release of USDA reports. In this thesis we took a different approach by analyzing the effect of stocks-to-use ratios gleamed from the release of monthly WASDE reports on futures spreads rather than on individual futures contracts. This approach ties this thesis into a related body of research that has examined the relationship between stocks and storage levels and futures price spreads – loosely referred to as the theory of storage.

Specifically, the purpose of this study is to analyze the price discovery role of Chinese and U.S. rice futures markets to reflect storage cost data and supply and demand information – summarized by stocks-to-use ratios – contained in WASDE rice reports published by USDA. We specify two models based upon theory of storage:

$$Futures\ spread = \alpha + \beta\ stocks/use\ \ ratio + \varepsilon \qquad (1)$$

$$Futures\ spread = \alpha + \beta 1\ stocks/use + \beta 2\ storage\ cost + \varepsilon \qquad (2)$$

where stocks/use ratio is a measurement of supply and demand derived from WASDE reports. The following regression model estimates were calculated using GLS-AR(1) approach for different types of rice:

$$Y_c = 0.36 + 0.87\, X_{1c}$$

$$Y_c = 0.47 + 1.18\, X_{1c} + 0X_{2c}$$

$$Y_u = 0.39 + 0.90\, X_{1r}$$

$$Y_u = -0.001 + 0.91\, X_{1r} + 0.51X_{2u}$$

$$Y_u = 0.38 + 0.91\, X_{1m}$$

$$Y_u = -0.05 + 0.92\, X_{1m} + 0.53X_{2u}$$

$$Y_u = 0.87 + 0.61\, X_{1l}$$

$$Y_u = 0.1 + 0.87\, X_{1l} + 0.39X_{2u}$$

$$Y_u = 0.81 + 0.43\, X_{1me}$$

$$Y_u = 0.48 + 0.42\, X_{1me} + 0.46X_{2u}$$

where Y_c is the futures spread in Chinese rice futures market, Y_u is the futures spread in U.S. rice futures market. X_{1c} is the stocks/use ratio in Chinese rice market. X_{1r}, X_{1m}, X_{1l}, and X_{1me} are rough rice stocks/use ratio in U.S. rice market, milled rice stocks/use ratio in U.S. rice market, long-grain rice stocks/use in U.S. rice market, and medium-rice stocks/use ratio in U.S. rice market. X_{2c} is the storage cost of Chinese early rice. X_{2u} stands for U.S. rice storage cost.

One of the main results of our regression analysis is that Chinese rice stocks/use ratio has positive linear relationship with Chinese early rice futures spread. We find no evidence that our estimated storage costs impact Chinese rice futures spreads. One potential reason for this result may be that almost all of the early rice storage facilities are run by Chinese government, and as such storage cost is very low with low interest rates.

Our model 1 results indicate that when the Chinese rice stocks/use ratio increases by 1 percent, on average Chinese early rice futures spreads will increase by 0.87 yuan per ton (RMB, 1 yuan = 0.162 dollars, based on the July 2014 exchange rate). This is just under the rice contract tick size. In other words, the deferred (two-month ahead) futures contract will trade an additional 0.87 yuan per ton higher than the nearby futures contract. Given that Chinese stocks-to-use ratios vary between 30.18 and 35.53 percent over our sample period, a 1 percent change in the stocks-to-use ratio would lead to a 0.87 yuan per ton change in the futures spread.

With respect to the U.S., we focus on model 2 results, which show significantly positive relationships between futures spreads and stocks-to-use ratios and between futures spreads and estimated storage costs. These results are consistent with the theory of storage. The size of stocks/use ratio effect varies based on different kinds of rice. Milled and long grain rough rice stocks/use ratio has the biggest effect on U.S. rough rice futures spread compared to medium-grain rice. On average, when the milled rice stocks/use ratio increases by 1 percent, U.S. rough rice futures spread will increase 0.92 cents per cwt. A 1 percent increase in long grain stocks-to-use ratio has a similar effect in terms of magnitude of 0.87 cents per cwt. However, a 1 percent increase in medium grain stocks-to-use ratio only increase futures spread by 0.42 cents cwt. A 1 cent per cwt increase in our estimated storage costs widens U.S. rough rice futures spread by around 0.5 cents per cwt. Given that total rough rice US stocks-to-use ratios vary

between 10 and 20 percent over our sample period (see Fig 9), a 10 percent change in the total rough rice stocks-to-use ratio – which could possibly occur from one crop year to the next – would lead to on average a 9 cents per cwt change in the futures spread. This would represent a large and economically significant price change in futures spreads.

In summary, our results show that U.S. rice futures market responds to supply and demand information and incorporate storage costs. U.S. rice futures market appears to be fulfilling its price discovery and storage role. Similarly, at least with respect to supply and demand information, Chines rice futures market spreads appear to follow theory of storage and respond to supply and demand information.

On a final note there are several important caveats and limitations to our study. First, futures spreads for different delivery periods may not be affected uniformly by stocks-to-use and storage. In this study by aggregating futures spread observations across different delivery periods we implicitly assumed that stocks-use-ratio information would have the same uniform impact on different spreads. Second, our storage costs estimates were approximated using nearby futures rather than cash prices of differing types of rice. Given that the futures are based upon long grain rough rice, this may not be an accurate reflection of medium grain rice storage costs. Third, given that our Chinese stocks-to-use and storage data cover a relatively short period of time and that both types of data are difficult to accurately measure (WASDE reports rely on the accuracy of Chinese government to report Chinese rice supply) – it is difficult to make conclusive general inferences from our Chinese results. Finally, our simple modeling approach may not adequately account for potential endogenous nature of futures and stock-to-use ratio data. In other words both variables may be considered as driving causality and movements in these variables are likely determined simultaneously. Zulauf, Zhou, and Roberts

(2005) attempt to address this concern by modeling futures spreads (adjusted for storage costs) and stocks-to-use ratios in a simultaneous equation system estimated using three stage least squares regression. Future work could address these caveats.

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Table 1. Chinese rice futures contract

Underlying Product	Early Long-grain Nonglutinous Rice
Contract Size	10 Tons
Price Quote	Yuan (RMB)/Ton
Tick Size	1 Yuan/Ton
Daily Price Limit	3% of above or below the previous trading day's settlement price and the relevant provisions of Zhengzhou Commodity Exchange Futures Trading Risk-control Regulation.
Contract Months	Jan, Mar, May, Jul, Sep and Nov
Trading Hours	Monday through Friday(Beijing time, legal holidays excepted) 9:00-11:30 a.m. 1:30-3:00 p.m.
Last Trading Day	The seventh business day prior to the last trading day in the contract month.
Delivery Date	The seventh business day prior to the last trading day in the contract month.
Deliverable Grades	Above 3rd grade (including 3rd grade) early long-grain nonglutinous rice (National standard Rice, GB1350-1999), and the early long-grain nonglutinous rice specified by Delivery Rules of ZCE. Substitutions at differentials see Delivery Rules of ZCE.
Delivery Place	Exchange-appointed delivery warehouses
The Lowest Margin Rate	5% of contract value
Trading Fees	2 Yuan/contract (including risk fund)
Delivery Method	Physical delivery
Ticker Symbol	ER
Listed Exchange	Zhengzhou Commodity Exchange

Source: Introduction of early rice futures contract (Zhengzhou Commodity Exchange)

Table 2. Limitation of trading volume of early rice futures contract

		Members of trading company	Members of non-trading company	Individuals
General months	More than 200,000 contracts trading in the market	15%	10%	5%
	Less than 200,000	30,000	20,000	10,000
The month before contract maturity month	First 10 days	18,000	4,800	2,400
	Second 10 days	10,000	3,600	1,800
	Last 10 days	6,000	2,400	1,000
Contract maturity month		3,000	1,000	500

Source: Introduction of early rice futures contract (Zhengzhou Commodity Exchange)

Table 3. U.S. rice futures contract

Underlying Product	Long grain rough rice
Contract Size	2,000 hundredweights (CWT) (~ 91 Metric Tons)
Price Quote	Cents per hundredweight
Tick Size	1/2 cent per hundredweight ($10.00 per contract)
Daily Price Limit	$1.10 (outrights) $2.20 (Calendar Spreads) for initial and expanded price limits. There shall be no price limits on the current month contract on or after the second business day preceding the first day of the delivery month.
Contract Months	January, March, May, July, September, and November
Trading Hours	Sunday – Friday, 7:00 p.m. – 7:45 a.m. CT and Monday – Friday, 8:30 a.m. – 1:15 p.m. CT (Electronic Platform) Monday – Friday, 8:30 a.m. – 1:15 p.m. CT(Open Outcry)
Last Trading Day	The business day prior to the 15th calendar day of the contract month
Delivery Date	Contracts mature in January, March, May, July, September, and November. Each contract month represents a separate futures contract
Deliverable Grades	U.S. No. 2 or better long grain rough rice with a total milling yield of not less than 65% including head rice of not less than 48%. Premiums and discounts are provided for each percent of head rice over or below 55%, and for each percent of broken rice over or below 15%. No heat-damaged kernels are permitted in a 500-gram sample and no stained kernels are permitted in a 500-gram sample. A maximum of 75 lightly discolored kernels are permitted in a 500-gram sample
Delivery Place	Designated elevators in Eastern Arkansas
Ticker Symbol	ZR (Electronic Platform)/RR(Open Outcry)
Listed Exchange	CBOT

Source from CME group

Table 4. Futures spread in Chinese and U.S. data set

Spreads in different numbers trading contracts*	Spreads in trading contracts**	Spread in U.S. futures	Spreads in Chinese futures
Y1	y_1	May-July	March-May
Y2	y_1	March-May	January-March
	y_2	May-July	March-May
Y3	y_1	January-March	November-January
	y_2	March-May	January-March
	y_3	May-July	March-May
Y4	y_1	November-January	September-November
	y_2	January-March	November-January
	y_3	March-May	January-March
	y_4	May-July	March-May

* In this column, Yi stands for the spreads in different futures spread categories. For example, Y4 stands for the spread in the futures spread category which has four spread traded simultaneously at any point in time during our data series.

** In this column, y_i stands for the ith spread traded in the different futures spread categories (Yi). For example, y_4 in Y4 stands for the 4^{th} spread traded in the category which has four spread traded simultaneously at any point in time during our data series.

Table 5. Regression analysis of Chinese and U.S. rice market using Normal Least Square and Generalized Least Squares

Model	Countries	Independent variables	Parameter estimates	Ordinary Least squares estimates (OLS)	P-value (OLS)	Generalized least squares estimates (GLS)	P-value (GLS)
Model1*	China	Chinese rice	α	-19.26	0.96	0.41	0.19
			β	1.94	0.86	0.83	<0.01
	U.S.	Rough rice	α	15.47	<0.01	0.05	0.73
			β	0.26	0.03	1.19	<0.01
		Milled rice	α	15.42	<0.01	0.04	0.77
			β	0.26	0.03	1.19	<0.01
		Long-grain	α	16.46	<0.01	0.48	<0.01
			β	0.23	0.02	1.00	<0.01
		Medium-grain	α	18.77	<0.01	0.32	0.01
			β	0.04	0.68	0.76	<0.01

*Model 1: $y = \alpha + \beta$ stocks/use ratio

Continued table 5.

Model	Countries	Independent variables	Parameter estimates	Ordinary Least squares estimates (OLS)	P-value (OLS)	Generalized least squares estimates (GLS)	P-value (GLS)
Model 2*	China	Chinese rice	α	236.43	0.53	0.42	0.2
			β1	-2.78	0.81	0.89	0.04
			β2	-4.90	0.07	-0.11	0.87
	U.S.	Rough rice	α	17.97	<0.01	-0.28	0.07
			β1	0.19	0.16	1.14	<0.01
			β2	-0.15	0.26	0.48	<0.01
		Milled rice	α	17.90	<0.01	-0.28	0.07
			β1	0.19	0.15	1.15	<0.01
			β2	-0.15	0.26	0.48	<0.01

*Model 2: $y = \alpha + \beta 1$ stocks/use ratio $+ \beta 2$ storage cost

Continued table 5.

Model	Countries	Independent variables	Parameter estimates	Ordinary Least squares estimates (OLS)	P-value (OLS)	Generalized least squares estimates (GLS)	P-value (GLS)
Model 2*	U.S.	Long-grain	α	18.51	<0.01	0.1	0.34
			β1	0.18	0.09	0.89	<0.01
			β2	-0.15	0.27	0.36	<0.01
		Medium-grain	α	21.49	<0.01	0.09	0.56
			β1	0.01	0.93	0.7	<0.01
			β2	-0.23	0.06	0.43	<0.01

*Model 2: $y = \alpha + \beta 1$ stocks/use ratio + $\beta 2$ storage cost

Table 6. Serial correlation correction of Generalized Least Square regressions

Model	Countries	Independent variables	Parameter estimates	Generalized least squares estimates (GLS)	P-value (GLS)	Durbin-Watson (GLS)	Parameter estimates AR(1) correction (AR)	P-value (AR)	Durbin-Watson (AR)
Model1 *	China	Chinese rice	α	0.41	0.19	1.10	0.36	0.45	2.05
			β	0.83	<0.01		0.87	0.01	
			AR1	-	-		0.45	<0.01	
	U.S.	Rough rice	α	0.05	0.73	1.33	0.39	0.03	2.06
			β	1.19	<0.01		0.90	<0.01	
			AR1	-	-		0.37	<0.01	
		Milled rice	α	0.04	0.77	1.33	0.38	0.03	2.05
			β	1.19	<0.01		0.91	<0.01	
			AR1	-	-		0.37	<0.01	

*Model 1: $y = \alpha + \beta$ stocks/use ratio

Continued table 6.

Model*	Countries	Independent variables	Parameter estimates	Generalized least squares estimates (GLS)	P-value (GLS)	Durbin-Watson (GLS)	Parameter estimates AR(1) correction (AR)	P-value (AR)	Durbin-Watson (AR)
Model1	U.S.	Long-grain	α	0.48	<0.01	1.25	0.87	<0.01	2.10
			β	1.00	<0.01		0.61	<0.01	
			AR1	-	-		0.43	<0.01	
		Medium-grain	α	0.32	0.01	1.25	0.81	<0.01	2.10
			β	0.76	<0.01		0.43	<0.01	
			AR1	-	-		0.43	<0.01	
Model 2	China	Chinese rice	α	0.42	0.2	1.10	0.47	0.34	2.06
			β1	0.89	0.04		1.18	0.04	
			β2	-0.11	0.87		-0.64	0.50	
			AR1	-	-		0.46	<0.01	

*Model 1: $y = \alpha + \beta$ stocks/use ratio, model 2: $y = \alpha + \beta 1$ stocks/use ratio + $\beta 2$ storage cost

Continued table 6.

Model	Countries	Independent variables	Parameter estimates	Generalized least squares estimates (GLS)	P-value (GLS)	Durbin-Watson (GLS)	Parameter estimates AR(1) correction (AR)	P-value (AR)	Durbin-Watson (AR)
Model 2*	U.S.	Rough rice	α	-0.28	0.07	1.36	-0.001	<0.01	2.04
			β1	1.14	<0.01		0.91	<0.01	
			β2	0.48	<0.01		0.51	<0.01	
			AR1	-	-		0.36	<0.01	
		Milled rice	α	-0.28	0.07	1.32	-0.05	0.83	2.04
			β1	1.15	<0.01		0.92	<0.01	
			β2	0.48	<0.01		0.53	<0.01	
			AR1	-	-		0.36	<0.01	

*Model 2: $y = \alpha + \beta 1$ stocks/use ratio $+ \beta 2$ storage cost

Continued table 6.

Model	Countries	Independent variables	Parameter estimates	Generalized least squares estimates (GLS)	P-value (GLS)	Durbin-Watson (GLS)	Parameter estimates AR(1) correction (PAR)	P-value (AR)	Durbin-Watson (AR)
Model 2*	U.S.	Long-grain	α	0.1	0.34	1.18	0.1	0.49	2.03
			β1	0.89	<0.01		0.87	<0.01	
			β2	0.36	<0.01		0.39	<0.01	
			AR1	-	-		0.41	<0.01	
		Medium-grain	α	0.09	0.56	1.22	0.48	0.02	2.09
			β1	0.7	<0.01		0.42	<0.01	
			β2	0.43	<0.01		0.46	0.01	
			AR1	-	-		0.43	<0.01	

*Model 2: y = α + β1 stocks/use ratio + β2 storage cost

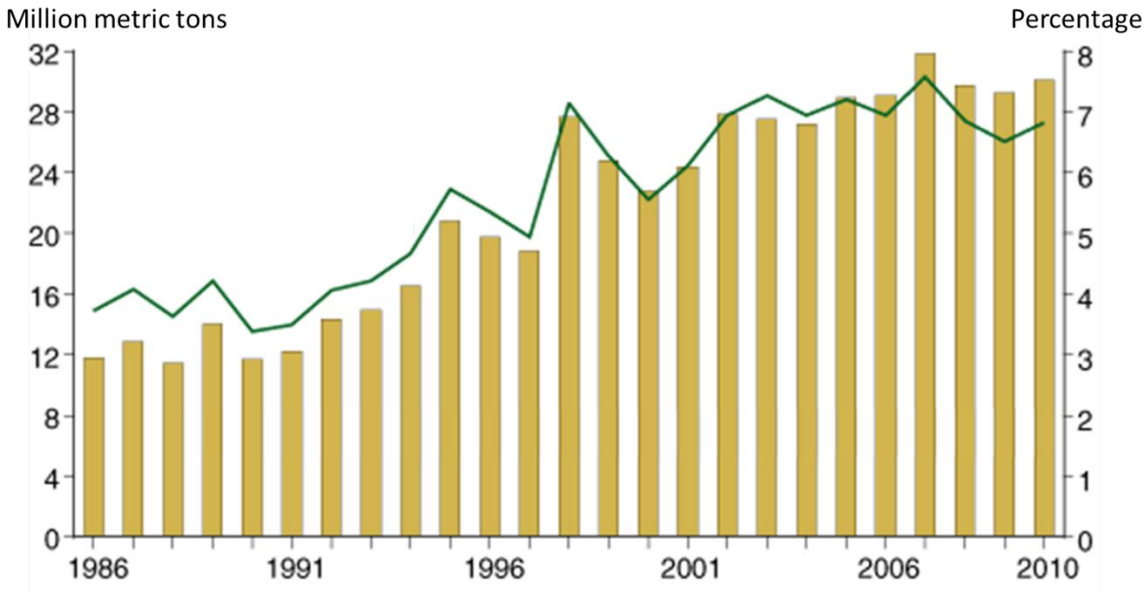

Fig. 1. Share of rice production and amounts of rice traded in the world rice market

Source: USDA, Economics Research Service, using data from USDA, Foreign Agricultural Service (Childs and Baldwin, 2010).

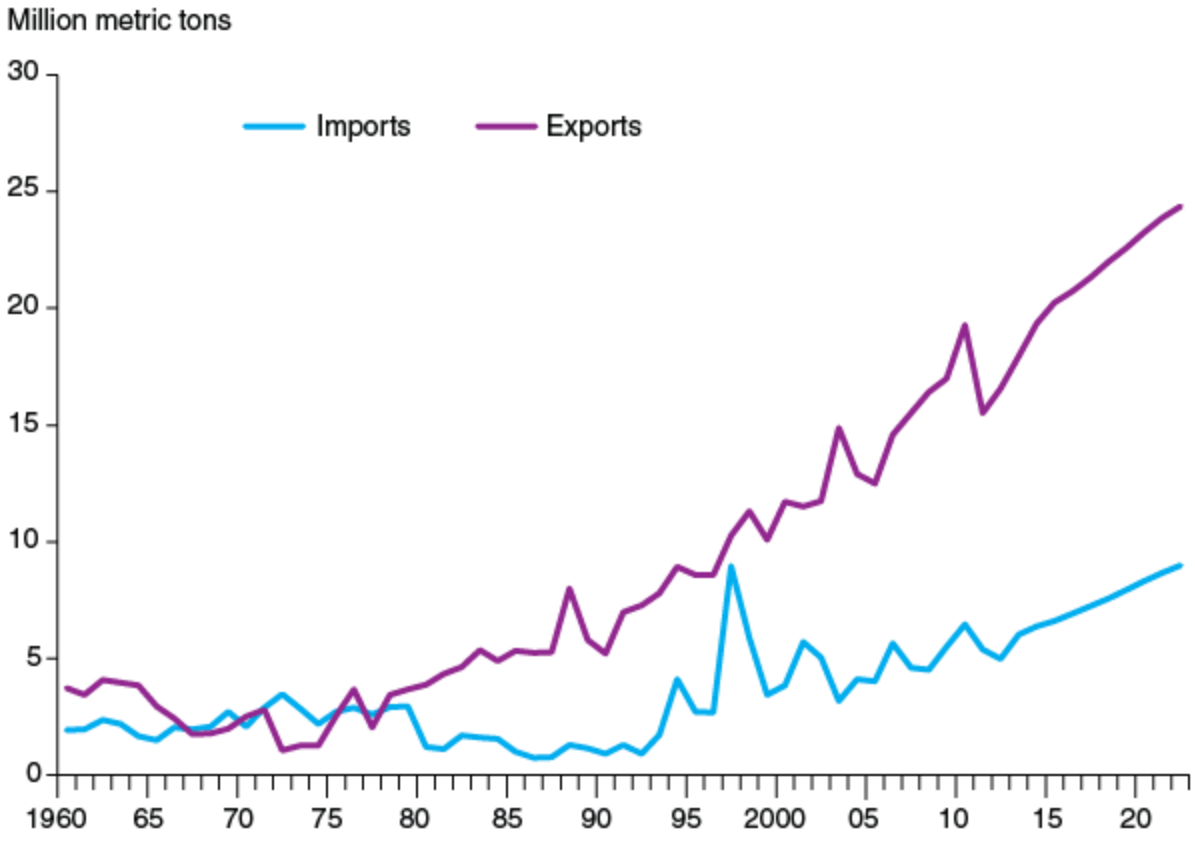

Fig. 2. Southeast Asia projected rice import and export

Source: USDA, Economic Research Service using USDA's production, supply, and distribution database for 1960-2013 and USDA's Baseline for 2014-22

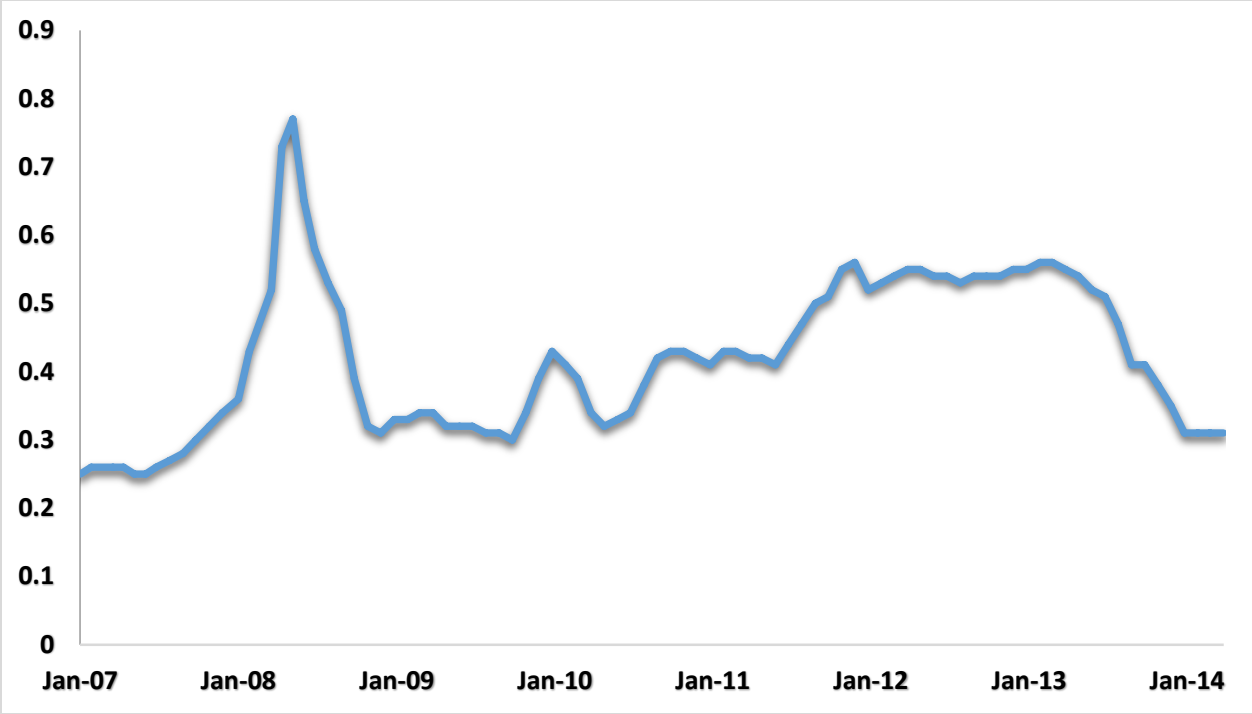

Fig 3. Rice global price (Dollars/Kg) (source from World Bank)

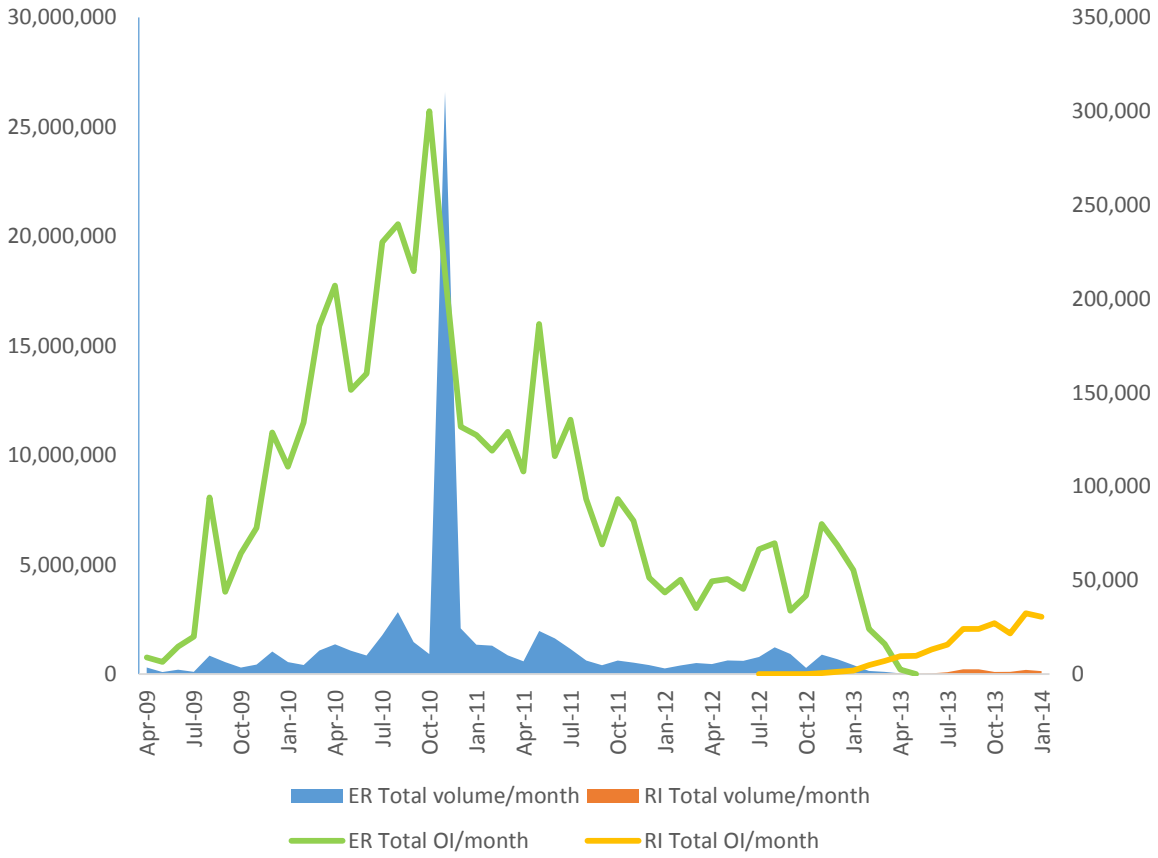

Fig 4. Trading volume and open interest of Chinese rice futures contract

Source: Trading database of early rice futures contract (Zhengzhou Commodity Exchange)

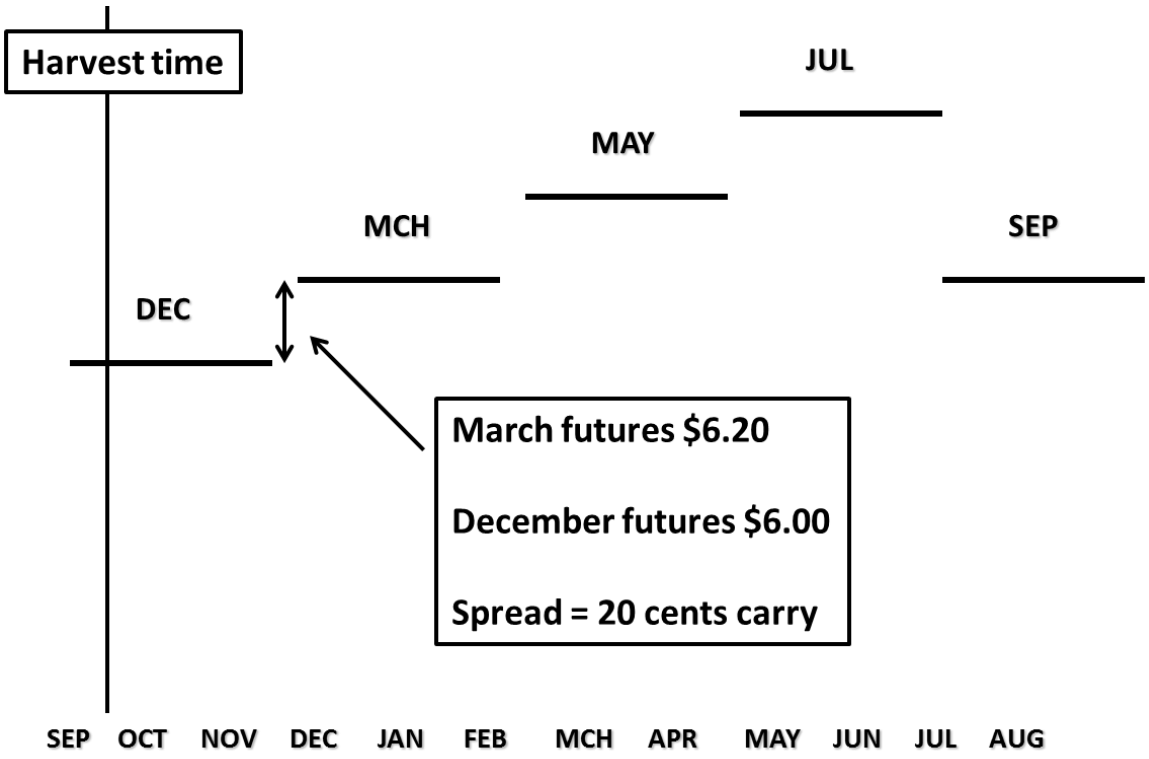

Fig 5. Futures spread demonstration

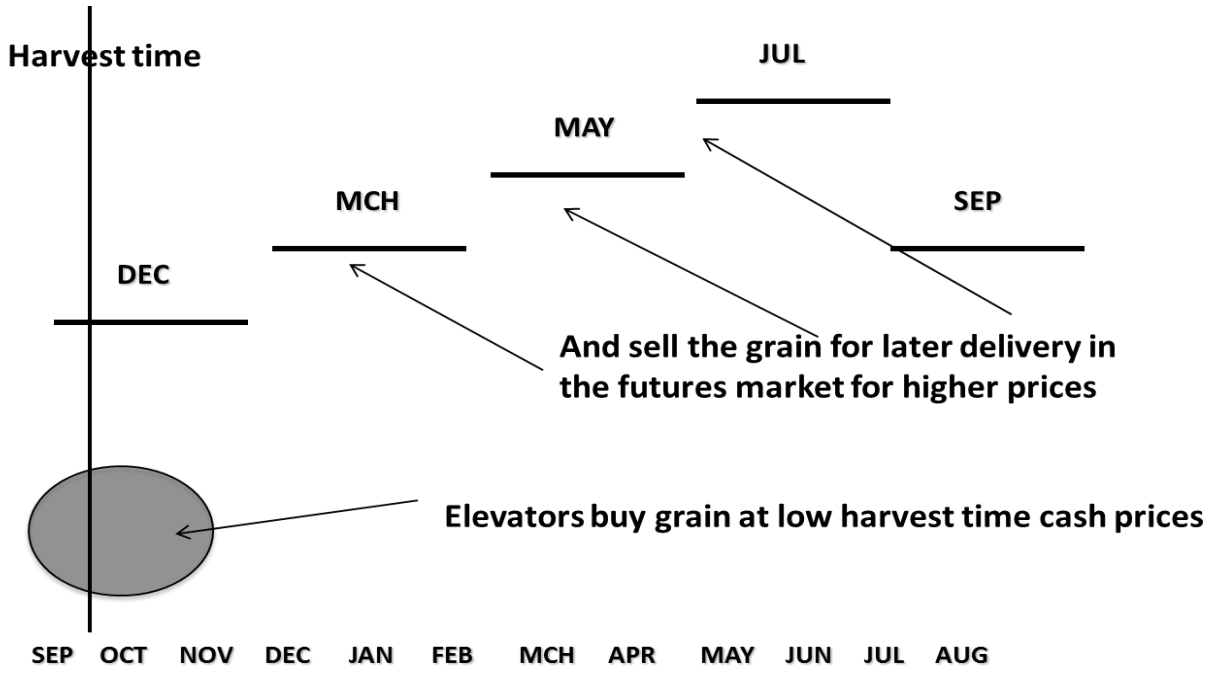

Fig 6. A carry stair-step pattern of futures price

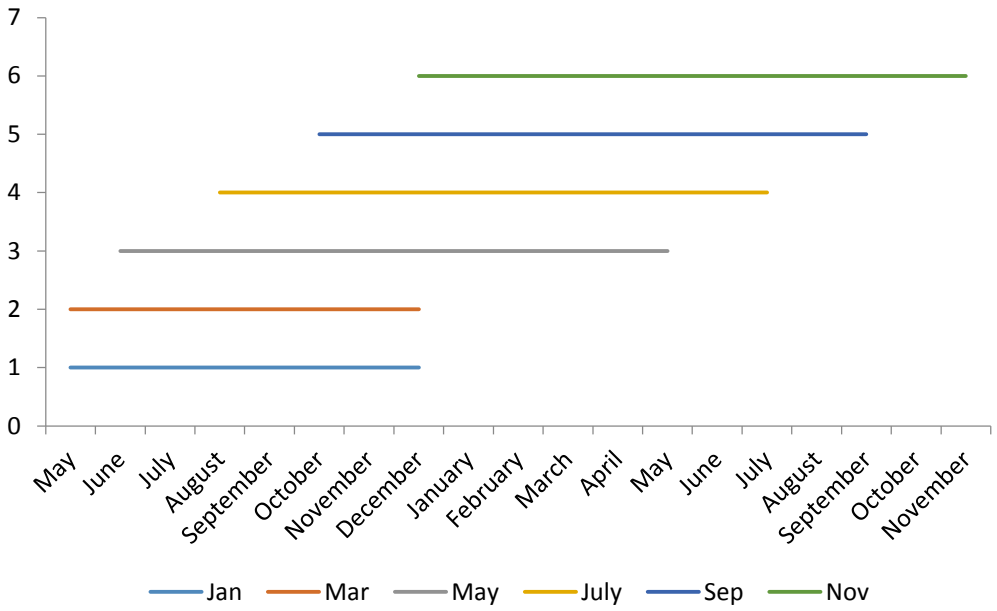

Fig 7. Overlapping futures contracts

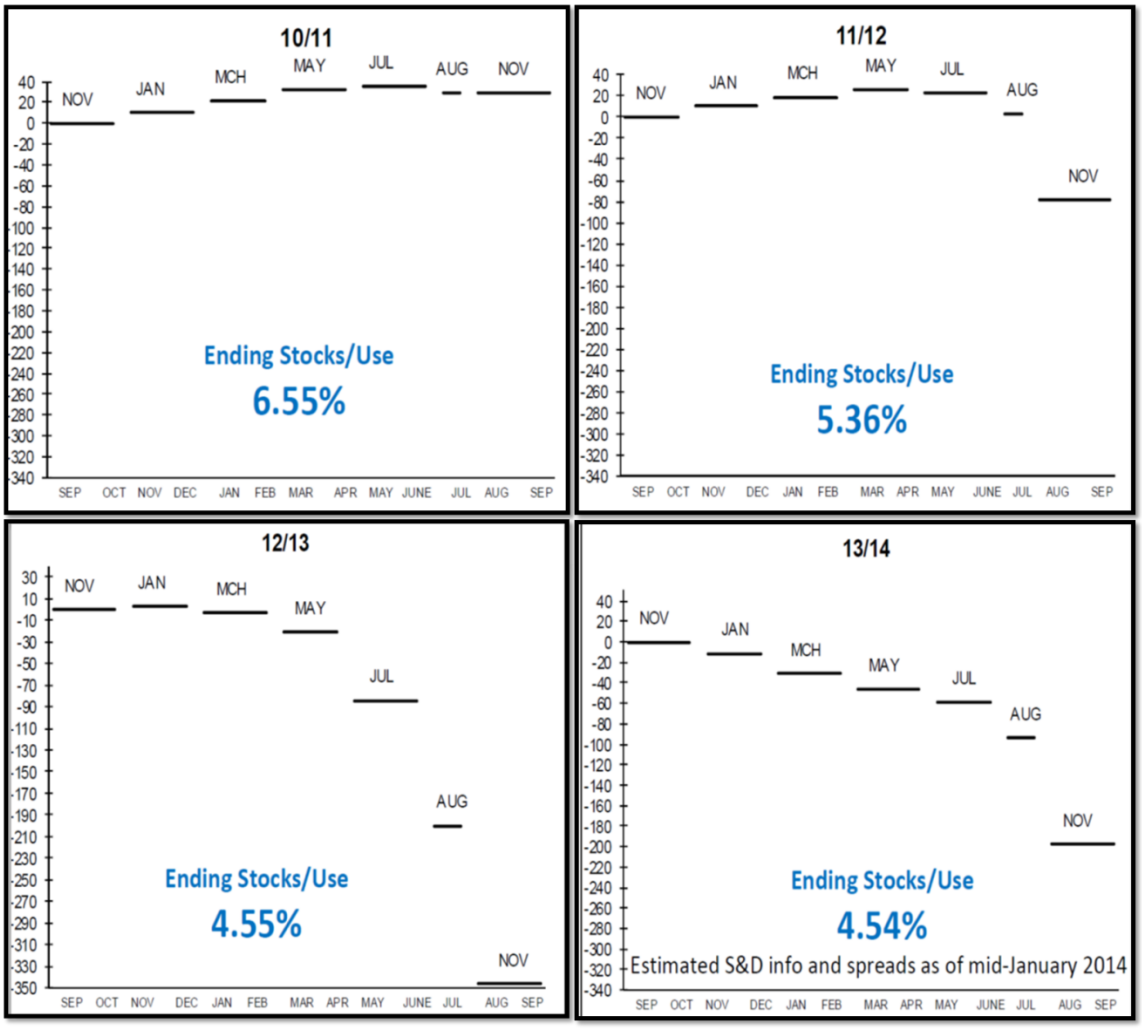

Fig 8. The relationship of ending stocks/use and futures spread in U.S. soybean futures market in 2010/2011, 2011/2012, 2012/13, 2013/2014 crop years. (Source from White Commercial Corporate)

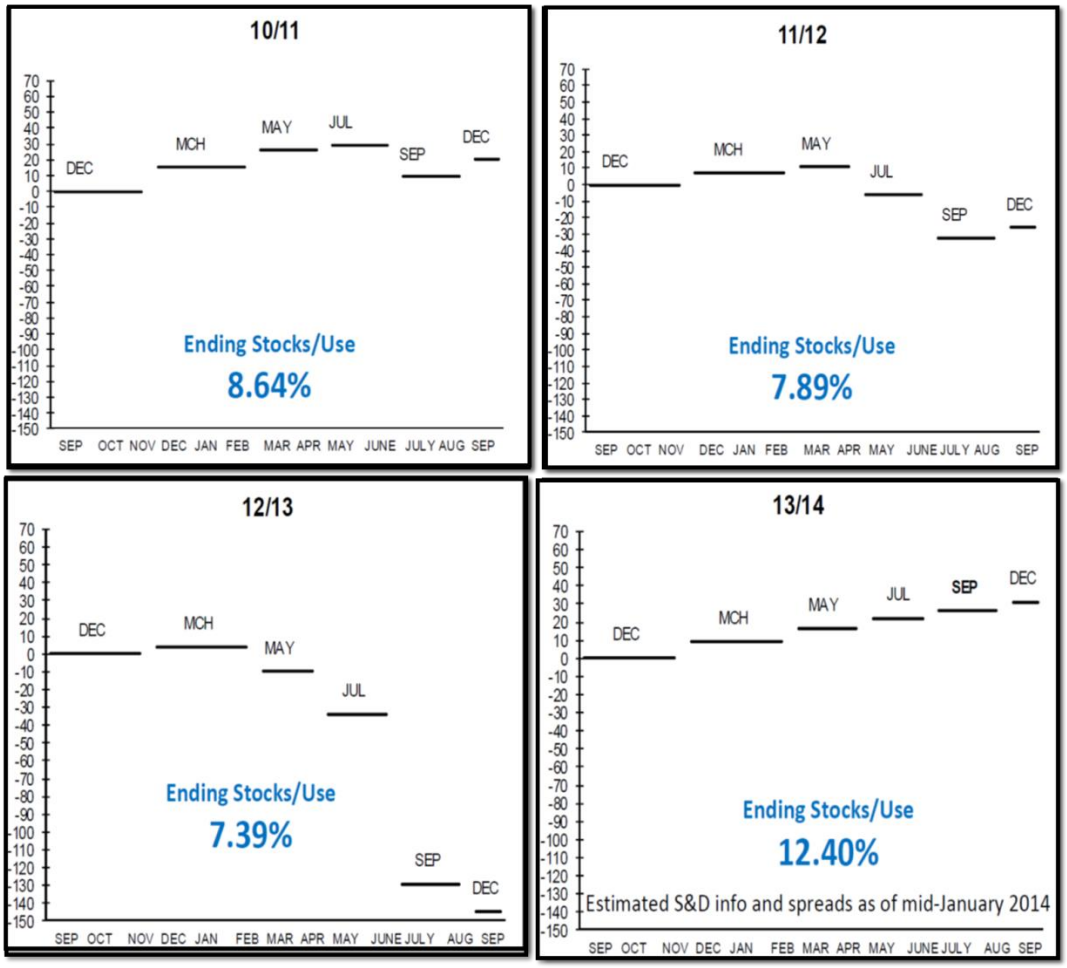

Fig 9. The relationship of ending stocks/use and futures spread in U.S. corn futures market in 2010/2011, 2011/2012, 2012/13, 2013/2014 crop years. (Source from White Commercial Corporate)

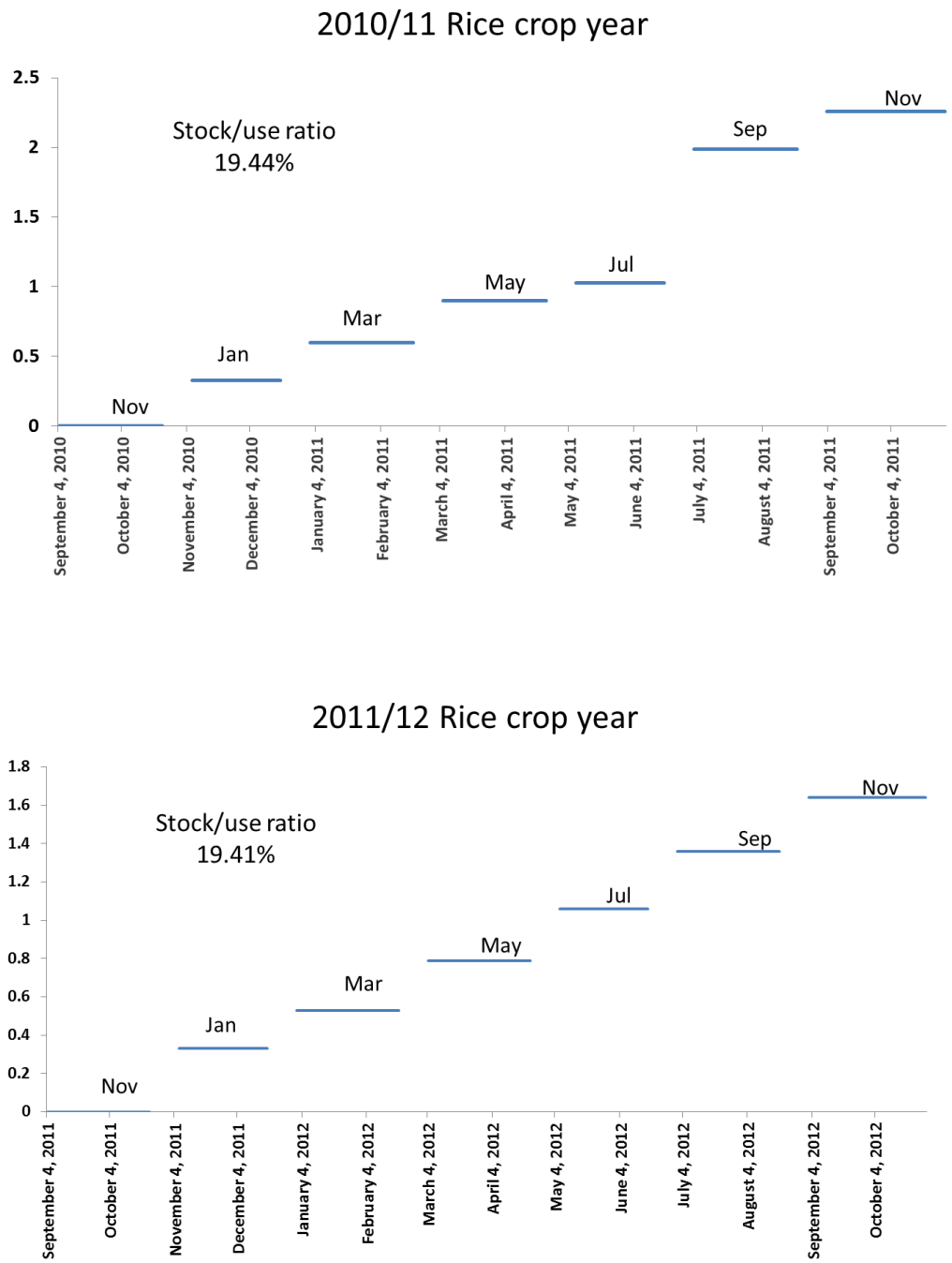

Fig 10. The relationship of ending stocks/use and futures spread in U.S. rice futures market in 2010/2011, 2011/12 crop years. (Source from White Commercial Corporation)

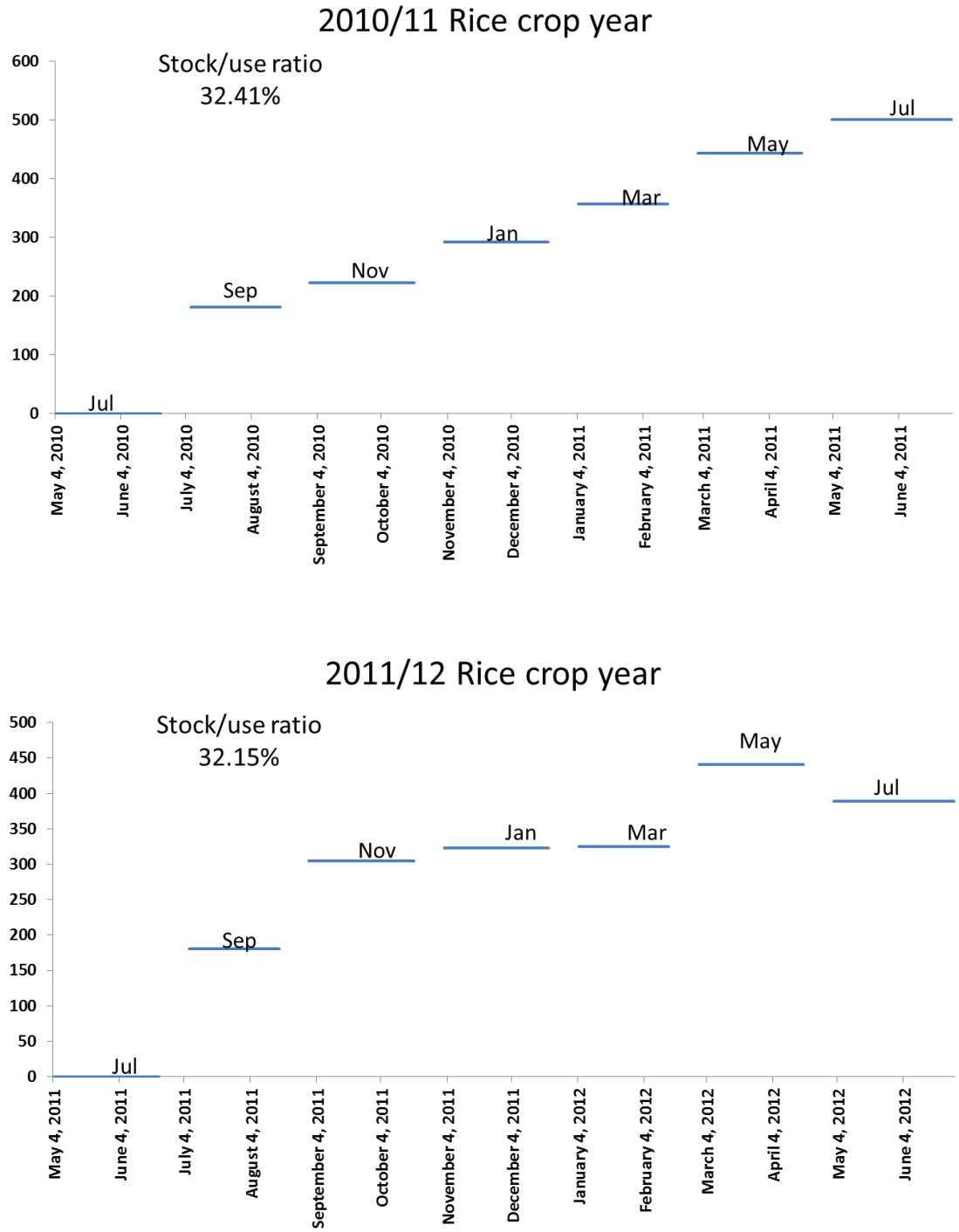

Fig 11. The relationship of ending stocks/use and futures spread in Chinese rice futures market in 2009/10, 2010/2011, 2011/12, 2012/13, 2013/14 crop years. (Source from White Commercial Corporation)