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The Co-movement between Non-GM and GM Soybean Price in China: Evidence from China Futures Market

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The price variability of agricultural commodities reached record levels in 2008, and again more recently in 2010, raising concerns about this increased price volatility would be temporal or structural. The Chinese soybean futures market is the second largest in the world in terms of trading volume. There are two soybean futures contracts in China: non-GM and GM. This study examines the volatility determinants as well as seasonality of non-GM and GM soybean futures prices traded in Dalian Commodity Exchange from 2005 to 2014. Also, we test the co-movement between these two soybeans markets. We analyze the volatility by incorporating changes in important economic variables into the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedastic (DCC-GARCH) model. This research provides statistical evidence that the futures prices of soybeans in China are being influenced by the increasing consumption of soybeans, the import quantity of soybean, the trading volume in futures market and weather.



1. Introduction

China is the world's largest producer and importer of non-GMO soybeans (Futures Industry Association, 2008). In China's domestic market, soybeans are a very significant agricultural commodity used as a major staple for human consumption, for conversion into human-consumable oil, and as an important animal feed ingredient. The price variability of agricultural commodities reached record levels in 2008, and again more recently in 2010 (Schnepf, 2008), raising concerns about this increased price volatility would be temporal or structural. The Chinese soybean futures market is the second largest in the world, after the CME group, in terms of trading volume. There are two soybean futures contracts in China: non-GM and GM. Due to its dominant market share of trading volume, the non-GM contract is the representative of China's soybean markets (He and Wang, 2011). However, the introduction of the new GM contracts in 2004 presents a number of new opportunities for hedging/managing/speculating price risk, but also presents new challenges because of the difficulty of measuring expected volatility.

Volatility is a directionless measure of the extent of the variability of a price, it is a numerical measure of the risk faced by individual investors and financial institutions. The biggest drawback of volatility is the associated uncertainty of marketing production, investment in technology, innovation etc. Increasing risk would lead to inefficient resource allocation for producers, merchandisers, and speculators, it also has the potential to limit access to food in developing countries that depend on imports and have lower incomes (OECD 2011). Therefore, it's significant to study the universal volatility law of agricultural futures market. To measure expected volatility, it is very important to understand the relationship between these two soybean,

their price determinants, and the underlying factors behind their price fluctuation. GM soybean is a close substitute of non-GM soybean, and therefore fluctuations in the price of GM soybean should result in corresponding fluctuations in non-GM soybean, vice versa. However, there is no literature before price volatilities of non-GM soybean and GM soybean are correlated or not. Consequently, it is important to analyze these two markets simultaneously to determine the factors behind their price volatility.

This research examines the influence of nine relevant factors on monthly soybeans futures prices. Price determinants include demand and supply factors. Macroeconomic factors affecting commodity prices have been studied in the literature. We use the industrial production index of China as a proxy of China's economic growth. Economic growth results in increased demand for goods, and therefore may generate an increase in demand for soybean. Weather plays an important role in the demand side of soybean markets. To capture the impact of weather, dummies for planting, growing, storage periods are used. On the supply side, storage levels are among the determinants of soybean prices. We use the ratio of stock and usage of soybean in China to account for this effect. Also, the production quantity of non-GM soybean in China is considered.

The estimation period covers a volatile period – the Global Financial Crisis – and it enables to assess the effect of changing economic conditions on the volatility of soybean. We made a specification with a dummy for this event. We also consider the speculative and hedging influences in China's futures market, represented by trading volume. Other variables found to affect soybean prices are included here, including crude oil price; the weighted exchange rate between China and three other major import partners, which are U.S., Brazil and Argentina; and

finally, the total import quantity of China from U.S., Brazil and Argentina is considered due to its large amount each year.

The purpose of this study is two-fold. First, we investigate the dynamic correlation across non-GM and GM soybean futures, with a focus on the persistency correlation across these two soybean futures prices traded on the Dalian Commodity Exchange. Further, Factors like percentage changes of industrial production index, trading volume, etc. are used to test whether they affect soybean price volatility. Our results can assist market participants better understanding which direction volatility in soybean go when levels of these factors change.

DCC-GARCH model is used to estimate volatility spillover effects and dynamic conditional correlation. Our study answers the following research questions: Does volatility in non-GM soybean prices have a spillover effect on the volatilities of GM soybean or vice versa? Which economic and natural factors most explain volatility in soybean markets? This study differentiates from previous studies in that it is the first to analyze the persistency of relation between non-GM and GM soybean futures prices in China.

This study can provide some knowledge of the conditions in Chinese agricultural commodity futures markets. Awareness of the origins and drivers of markets interaction help investors, consumers and regulators. It also contributes to securities pricing, portfolio optimization, developing hedging and regulatory strategies, etc. It is also in the interests of international market participants from countries like Canada, the USA, Australia and the European Union, who are the major grain exporters to China. In addition, the finding of this paper has relevant policy implications in asset allocation and risk management in designing agricultural commodity portfolios for investment decisions.

The study finds that the two soybean futures have high persistency. In addition, the study finds that the time-varying conditional correlation between non-GM and GM soybean futures is influenced by trading volume, ratio of stock and use, Chinese production and import level and the financial crisis. It also shows high volatility in the growing season.

2. Literature Review

In the last decade, many researchers offer contributions to finance agricultural research by explaining the volatility process. Kenyon et al. (1987) show that corn, soybeans, and wheat futures price volatility is affected by seasons, lagged volatility, and loan rates. Sørensen (2002) considers seasonal price patterns for corn, soybeans, and wheat futures, and concludes that the seasonal components for all three commodities peak about two to three months before the beginning of harvest. For the literature on how fundamentals affect volatility, it has been established that volatility is time-varying (Koekebakker and Lien 2004), highly persistent (Jin and Frechette 2004), and that, at least for grains and oilseeds, it is affected by supply and demand inflexibilities (Hennessy and Wahl 1996). Karali and Thurman (2010) investigate the determinants of daily price volatility in U.S. corn, soybeans, wheat, and oats futures markets and identify two significant factors Samuelson effect and the strong seasonality. Chen et al. (2010) found that exchange rates are very useful in forecasting future commodity prices but not vice versa. They also found positive relationship between exchange rate and international commodity prices.

More recent studies consider a time period when China had already developed its futures market and become the largest soybean importer. The results by Liu (2002) suggest that the large-volume trading is an important source of futures volatility in the Chinese soybean futures

market. Chan *et al* studied China's soybean, wheat and other futures markets, and found that negative returns appear to have a greater impact on volatility than positive returns do, while volume has a positive effect on volatility (Chan et al., 2004). Hernandez (2012) found that the variability of oil spot prices, soybean imports to China, and the number of index funds are able to explain monthly soybeans future price volatility, from September 2006 to August 2011.

Many researchers apply the ARCH-family volatility model in financial market, particularly in commodity market, such as Oglend and Sikveland (2008), Huang et al. (2009). Co-movement of commodity prices received substantial attention in economic literature. For example, applying a Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedastic (DCC-GARCH) analysis on a daily return series for the period 1997 to 2010, Dajcman et al. (2012) examines the co-movement dynamics between the developed European stock markets of the United Kingdom, Germany, France and Austria. The author's find that the co-movements between stock market returns are time varying and scale dependent and financial crisis in the observed period did not uniformly increase co-movement between stock market returns across all scales. However, little effort has been dedicated to the study of the joint movements among the prices of non-GM and GM soybean.

3. Model

The goal of GARCH models is to provide a measure of volatility. One of the earliest volatility models, autoregressive conditional heteroscedastic (ARCH), was proposed by Engle (1982), which captured the time-varying conditional variances of time series based on past information. This model was then enhanced by Bollerslev (1986) who proposed a generalized ARCH (GARCH) which took into account both past error terms and conditional variances into its

variance equation simultaneously to avoid the problem that the number of parameters to be estimated becomes too large as the number of lagging periods to be considered increases in the ARCH model. It has been shown that commodity futures prices also exhibit time-varying and can be effectively studied using GARCH models (Myers and Hanson, 1993; Goodwin and Schnepf, 2000).

Bollerslev (1990) further extended the GARCH model in a multivariate sense to propose a Constant Conditional Correlation Multivariate GARCH (CCC-GARCH) model where the conditional correlation amongst different variables were assumed to be constant, this may be inconsistent with reality (Longin and Solnik, 1995, 2001). Therefore, Engle (2002) finally proposed an DCC-GARCH model where the conditional correlations amongst variables were allowed to be dynamic by including a time dependent component in the conditional correlation matrix.

The main merit of DCC-GARCH model in relation to other time varying estimation methods is that it accounts for changes in both the mean and variance of the time series. Another advantage of DCC-GARCH model is that DCC-GARCH model estimates correlation coefficients of the standardized residuals and so accounts for heteroscedasticity directly (Chiang et al., 2007). Also, DCC-GARCH has the ability to adopt a student-t distribution of variances, which is more appropriate in capturing the fat-tailed nature of the distribution of index returns (Pesaran and Pesaran, 2009). This choice allows to estimate time-varying correlations of returns with heavy tails.

The DCC-GARCH approach has been widely used in recent papers investigating notably the linkages between bond prices (Antonakakis, 2012), stock prices (Cai, Chou and Li, 2009 or Bali

and Engle, 2010), stock and bond prices (Yang, Zhou and Wang, 2009) with an extension to commodity futures (Silvennoinen and Thorp, 2013) or to commodity prices (Creti, Joets and Mignon, 2013). We adopt the bivariate DCC-GARCH model in our study and modify it to include exogenous variables that might have an impact on the conditional volatility.

We measure the monthly return from holding a futures contract on month t as

$$r_t = 100 \times (\ln F_t - \ln F_{t-1}) \quad (1)$$

where F_t is monthly settlement price of the futures contract on the last day of month t .

Assume that soybean market returns from the two series are bivariate normally distributed with zero mean and conditional variance-covariance matrix H_t , our bivariate DCC-GARCH model can be presented as follows:

$$\begin{cases} r_t = \mu_t + \varepsilon_t | I_{t-1} \rightarrow N(0, H_t) \\ H_t \equiv D_t R_t D_t + G' G X_t \end{cases} \quad (2)$$

Meanwhile, the returns on the soybeans is fat tailed or leptokurtic where a normal distribution assumption is not appropriate. Our remedy for this is to use a Student-t distribution setting. That is, the conditional distribution $u_t | \Omega_{t-1} \rightarrow f_{Student-t}(u_t; \nu)$, where ν is the degree of freedom parameter.

In these formulars, r_t is the (2×1) vector of the returns on soybean prices; ε_t is a (2×1) vector of zero mean return innovations conditional on the information available at time $t-1$; $\mu_{i,t} = \delta_{i0} + \delta_{i1} r_{i,t-1}$ for market i ; G is the (2×2) lower triangular coefficient matrix on the exogenous variable X_t ; D_t is a (2×2) diagonal matrix with elements on its main diagonal being

the conditional standard deviations of the returns on each market in the sample and R_t is the

(2×2) conditional correlation matrix. D_t and R_t are defined as follows:

$$D_t = \text{diag}(h_{11t}^{1/2} \dots h_{22t}^{1/2}) \quad (3)$$

where h_{iit} is chosen to be a univariate GARCH (1,1) process;

$$R_t = (\text{diag} Q_t)^{-1/2} Q_t (\text{diag} Q_t)^{-1/2} \quad (4)$$

where $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1}$ refers to a (2×2) symmetric positive definite matrix with $u_{it} = \varepsilon_{it} / \sqrt{h_{iit}}$, \bar{Q} is the (2×2) unconditional variance matrix of u_t , and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$.

The DCC model is constructed to permit a two-stage estimation of H_t . During the first step, a univariate GARCH model is fitted for each of the assets and the estimates of h_{iit} are obtained. In the second step, the asset returns are transformed by their estimated deviations and used to calculate the parameters of the conditional correlation. The log-likelihood function for the DCC model can be written as follows:

$$L = -\frac{1}{2} \sum_t (k \log(2\pi) + \log |H_t| + r'_t H_t^{-1} r_t) \quad (5)$$

The conditional correlation coefficient ρ_{ij} between two markets i and j is then expressed by the following equation:

$$\rho = \frac{(1 - \alpha - \beta)\bar{q}_{ij} + \alpha u_{i,t-1} u_{j,t-1} + \beta q_{ij,t-1}}{\left((1 - \alpha - \beta)\bar{q}_{ii} + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1} \right)^{1/2} \left((1 - \alpha - \beta)\bar{q}_{jj} + \alpha u_{j,t-1}^2 + \beta q_{jj,t-1} \right)^{1/2}} \quad (6)$$

In this formulation, q_{ij} refers to the element located in the i th row and j th column of the symmetric positive definite matrix Q_i .

4. Data

We study non-GM and GM futures contracts that are traded on the Dalian Commodity Exchange (DCE). Both futures contracts have expiry dates in January, March, May, July, September and November. They are traded until the 10th trading day of the delivery month. Standard contract size is 10 metric tons and price is quoted as CNY per metric ton. We construct price daily time series for both soybeans by rolling over the third nearby contracts. When the futures price moves into the maturity month, we use the futures price for the next maturity month. We then use the price of the last day of the month as the proxy for the monthly soybean price. Futures price data are obtained from Datastream 5.1 provided by Thomson Reuters. Our sample covers the period from January 2005 to January 2014.

Commodity price volatility has been attributed to a number of factors, including demand and supply factors. Also, factors such as the integration of energy markets, macroeconomic conditions, and financial speculation all have been identified as key drivers of commodity price volatility (Masters and White 2008; Mitchell 2008; Irwin et al. 2008, 2009, 2010; Tangermann 2011). The following factors are considered as potentially overriding the factors leading to volatility of soybean prices in China's market. All these variables are recorded monthly and not seasonal adjusted.

For the macroeconomic factors, industrial production index is used to represent the Chinese macro-economic environment. Further, changes in exchange rates may reallocate purchasing power and price incentives across countries without changing the overall food supply–demand

balance. Here we use the weighted average of the foreign exchange value of the CNY, which is based on the value of CNY compared to the currencies of major China trading partners of soybeans, which are U.S. (Dollar), Brazil(Brazil) and Argentinian (Peso). Here we include percentage changes in "Industrial production index" and "weighted average of the foreign exchange value of the CNY" in the DCC GARCH model. The data utilized is obtained from DATASTRAM, FRED and the Central Bank of Argentina.

Inventory can reduce volatility so long as stocks are accumulated in periods of excess supply and released in times of excess demand. Because the important role inventories play in stabilizing demand and supply shocks, we include inventory data in our volatility analysis. We use the percentage change of stocks-to-use ratio computed with the series of “Ending Stocks” and “Total Use” of soybean of China published in World Agricultural Supply and Demand Estimates (WASDE) reports released monthly by the World Agricultural Outlook Board of USDA. Also, since China's soybean crop has been unable to keep pace with the rapid growth of domestic consumption, imports have grown rapidly to make up for the lack of domestic supply. The increasing deficit has been replaced by imports from Argentina, Brazil, and the U.S. These countries export approximately 90 percent of the world’s soybeans. More importantly, China will consume 60 percent of all exported soybeans by 2011(USDA). We use the percentage change of the summation from these three countries as the proxy from China's soybean imports. In recent years, there has been special interest regarding the relationship between energy markets and agricultural commodity prices. The integration between energy and agricultural markets is accounted for via oil spot prices. We use the percentage change of crude oil price stated in Dollars per Barrel from U.S. Energy Information Administration.

We also consider the speculative and hedging influences in China's futures market, represented by trading volume. Trading volume can be used as a proxy for information flows. Trading volume is likely to be associated with speculation, since day traders or speculators trade in and out in short periods of time, and seldom hold a position for too long. Fung and Patterson (2001) find that volume increases volatility. We use the percentage change of the total volume as the exogenous variables.

Dummy variables are used to account for the seasonal effects. We use three dummies to represent planting, growing and harvesting season. Inventory season is used as base categories and thus its impact is shown in the intercept. In general, volatility increases in the spring, peaks in the summer, and declines toward the end of a year. Yang and Brorsen (1993), Chatrath *et al.* (2002) and Adrangi and Chatrath (2003) all conform seasonality effect in futures market. The world financial crisis became prevalent on September 15, 2008 when the major investment bank Lehman Brothers announced that it will be filing for bankruptcy. This caused many ripple effects in the financial markets, causing a credit constraint for firms and consumers. This may have effect on the volatility of the commodity markets as well. For this event, our variable CRISIS takes the value of one on the dates between September 15, 2008 and June 30, 2009 and zero for the rest.

[Insert Figure 1]

Figure 1 shows the monthly returns to the non-GM and GM soybeans, for which the correlation coefficient is 0.81. As expected, there is a positive correlation between the returns of soybean markets. The values of the unconditional correlations are somewhat high. Clearly the series show a great deal of variation. The non-GM soybean shows greater variation than GM.

One may see that during the second half of year 2008, the returns exhibits high volatility, reflecting a financial crisis, after that, the correction can be seen in both markets. Table 1 presents descriptive statistics of the monthly returns and macro and economic variables employed in the empirical analysis. Table 2 shows the unit root test results for futures price series. As can be seen in the table, both the levels and the logs of futures prices in all markets contain a unit root, that is, these series are non-stationary. However, we can reject the existence of a unit root for the return series, computed as the differences of log futures prices.

[Insert Table 1, Table 2]

5. Empirical Results

In estimating our DCC-GARCH model for the two soybean futures, we first experiment the model with one lag, two lags, and three lags returns in the mean equation. Conditional variance equations include ARCH, GARCH parameters as well as exogenous variables discussed earlier that might have impact on volatility. To determine the appropriate length of lags, we computed the Akaike information criterion (AIC) for each model. For both soybean contracts, the one-lag model has the smallest AIC, and hence it was selected and reported here as the appropriate model. Table 3 presents the coefficient estimates and their p-values from the DCC-GARCH model. The statistical significance in this table is not indicated by asterisks, but rather by the p-value that are in parentheses under the estimates.

[Insert Table 3]

5.1 Non-GM Soybean

The mean equation results show a constant return of -0.008, but it is not significant. The first lagged returns is significant with a positive coefficient. The constant conditional variance is 2.006. The ARCH parameter of 0.313 implies that positive disturbances (shocks, news) to non-GM soybean increase conditional variance by that amount. The GARCH parameter for non-GM soybean is 0.224, showing that non-GM soybean volatility in the past period has some effect on volatility in the current period and is persistent.

Conditional variance results show that the World financial Crisis resulted in an increase in non-GM soybean price volatility. This event increases the conditional variance by 1.85 percent. For the macro variables, percent changes in FX and IPI both have insignificant effects on the conditional variance of non-GM soybean returns. A reason that the weighted FX does not influence monthly soybeans futures price volatility is that the currency CNY move relatively at the same pace of the three other currencies. This IPI does have a significant effect could be the result that non-GM soybean is a daily commodity in China and the demand for soybean is not effected much by the macro-economic environment. Additionally, lagged shocks in GM market does not show significant effect on non-GM market.

For the speculation behavior, both percent change in non-GM and GM soybean total trading volume have significant effects on the conditional variance of non-GM soybean returns. For a one-percent increase in total trading volume of non-GM soybean, the conditional variance increase by 1.09 percent, while for a one-percent increase in GM soybean volume, the variance increases by 0.1 percent. The positive effect of volume (a proxy for speculative activity) is consistent with results in the literature. For the demand/supply side variables, both the percent

change of stock/use ratio in China and the import quantity of China have significant effect on the variance as we expected. A one-percent change in the soybean stock/use ratio increases the variance by 4.75 percent while for a one-percent change in import quantity, the conditional variance of non-GM soybean decreases by 3.28 percent. Interestingly, the percent change of production of China is not statistically significant. This may due to the significant increase of soybean imports by China since the fourth quarter of 2006 has far exceeded the increase of the domestic production of China. The changes in percent change of crude oil price is not significant, either. This result agree with those obtained by Du et al. (2009), who concluded that there is no statistical evidence that the oil prices affect the variability of soybeans prices, but disagree with those obtained by Mitchell (2008) and Saghaian (2010). For the seasonality factors, only the dummy for growing time is found to be significant, showing higher volatility compared to other time. Thus we can tell that weather plays an important role in the non-GM soybean volatility in China.

5.2 GM Soybean

GM soybean futures have a constant return of -0.12 which is not significant. The coefficient on the first lagged return is positive. The constant conditional variance is 2.2. The ARCH parameter is 0.21 and statistically significant. The GARCH parameter is 0.21, showing a small level of persistence. Similar to non-GM soybean, the financial crisis in 2008 is found to have significant impact on the conditional variance of GM soybean futures. Due to this crisis, the GM soybean variance increased by 2.92 percent, which bigger than the increase of non-GM soybean variance. This is probably because that China produces only 20% of its soybean consumption and most soybean imports are Genetic Modified. The crisis has caused severe influences in the

international commodity market, the international trade of soybean thus been affected. Among macro variables, neither FX or IPI are significant, which is the same as the results for non-GM soybean. For the speculation behavior, both the trading volume of non-GM and GM soybean have a significant positive effect on variances of GM soybean.

Different from non-GM soybean, the factor of production of China shows significant effects on variances of GM soybean. A one-percent increase in production decreases the conditional variances by 20.2 percent, while a one-percent increase in stock/use ratio and import quantity in China increase the variances by 5 percent and decrease by 2.3 percent respectively. There is a huge effect of the production quantity on the volatility of GM soybean, which we can conclude the price of the imported product largely depend on the production power of the domestic product. Interestingly, the crude oil price is not statistically significant. Same as non-GM soybean, for the seasonal effect, only the growing season has significant negative effect on conditional variance. Additionally, the lagged shock of non-GM market is found to increase the conditional variance of GM soybean by 0.13, showing spillover effects from non-GM to GM soybean market.

5.3 Comovement

Finally we turn to the DCC components. The effect of time-varying correlation is captured by the coefficient DCC(1) and DCC(2), which are the parameters governing the DDC-GARCH process. DCC(1) is the sensitivity of correlations due to shocks, it reveals the speed at which the correlations matrix changes; while DCC (2) shows the persistence in the dynamic correlation, with 1 being constant correlations.

The DCC parameters in our model are significant at the 1% level, revealing that the correlation has a dynamic component. Wald test rejects the null hypothesis that $DCC(1)=DCC(2)=0$ at all levels ($\chi^2 = 1102.45$) and p-value = 0.000. The DCC(1) has an estimated value of 0.261, means the correlation is sensitive due to shocks, but not very big. DCC(2) is estimated to be 0.78. This means that there is a relatively high level of persistence over time in the correlation between these two soybeans, which is consistent with what we see in the graph. In summary, the dynamic volatilities in the returns in non-GM soybean and GM soybean markets are generally interdependent over time, sometimes very strongly.

[Insert Figure 2]

Estimated dynamic conditional correlations within soybean markets plotted in Figure 2. The average time-varying correlations are quite similar to the unconditional correlations reported earlier which is 0.8. The expected high to positive relationship between non-GM and GM soybeans is evident. The stable near 0.9 correlation between non-GM and GM soybeans breaks down sharply in early 2008, however, still positive and remaining so for the remaining two years. After the crisis, the correlation starts to rise in 2010 and keep the 0.9 level again till 2012. Then the correlation begins to drop again in 2013. Figure 2 confirms the time-varying properties of correlations.

6. Conclusion

The DCE non-GMO soybean contract is the first market price series with sufficient information to appropriately model a price integration linkage for an IP market in China. Because of the large amount of GMO soybeans imported, market participants start to pay more attention to the GMO

futures markets. This paper analyzes the dynamic conditional correlations in the returns on these two soybean prices using multivariate DCC-GARCH model. The dynamic correlations enable a determination of whether the non-GM and GM returns are substitutes or complements, which can be used as trading strategies. Further, we analyze the impact of major economic variables on the volatility in these markets. This research provides statistical evidence that the futures prices of soybeans in China are being influenced by the increasing consumption of soybeans, the import quantity of soybean, the trading volume in futures market and weather condition during the growing season of soybean. Soybeans price volatility has important implications for producers, traders, and consumers. For both soybean contracts, we find some volatility persistence—as measured by the response to lagged absolute change—the effects are not large. We find statistically significant persistence in the form of an ARCH effect. The ARCH coefficients are relatively small in size, which indicates that conditional volatility does not change very rapidly. The GARCH are not very large, either, indicating weak gradual fluctuations over time. Spillover effect was found from non-GM market to GM market.

The results of this study reveal that there is insufficient evidence to show that soybeans imports to China influenced monthly soybeans futures price volatility. For the speculation behavior, both the trading volume of non-GM and GM soybean have a significant positive effect on variances of the soybeans volatility. Among the macroeconomic variables considered, neither the IPI or FX affect the volatility of the two soybeans. We found the positive effect the percentage change of stock/use ratio on volatility in both soybean markets. Volatility in soybean markets is also found to change in response to the financial crisis event. The financial crisis increased both the two soybean price returns. The impact of negative shocks on GM soybean

variance is larger than the impact of negative shocks in the non-GM soybean variance. China's soybean market is found to exhibit some seasonality with higher volatility in the growing season, which is from July through August. (INTA, 2011)

Knowledge of the co-movements of soybean returns and volatilities is important in constructing optimal hedging and trading strategies, asset allocation and risk management. The price movements of soybeans influence the activity of traders in three ways. First, the price volatility will influence the level of capital or credit that will be required of dealers to buy and store crops; second, the price level will affect the amount of capital or credits needed to maintain margin accounts for hedging activities, and finally, the price volatility will increase the risk of non-performance on producer contracts. Also, the pattern of price movements has an impact on managerial decisions of soybeans producers. First, increasing volatility will affect the level of profit and the value of the land used for production. Second, large variation of prices affects the level of revenue protection, and hence the cost of revenue insurance.

For practical purposes, our study will be helpful for understanding the value of other newly developed markets where the product traded is a close substitute for an existing market. In addition to adequate monetary policy, regulations are very much necessary to be created and/or enforced in order to prevent another financial calamity, as soybean volatilities were highly affected by the 2008 U.S. financial crisis.

Table 1. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
NonGM Soybean Return	0.571	5.008	-16.965	12.684
GM Soybean Return	0.464	6.028	-18.02	24.484
%ΔNonGM Soybean Volume	0.186	0.828	-0.891	3.465
%ΔGM Soybean Volume	0.534	3.267	-0.898	32.417
%ΔNonGM Soybean Open Interest	0.014	0.227	-0.415	1.452
%ΔGM Soybean Open Interest	0.217	1.26	-0.95	11.46
%ΔChina Soybean Production	-0.003	0.023	-0.077	0.119
%ΔChina Soybean Import	0.05	0.29	-0.549	1.321
%ΔChina use/stock	-0.00036	0.106	-0.359	0.63
%ΔChina IPI	-0.001	0.022	-0.11	0.07
%ΔU.S. Soybean Production	0.001	0.036	-0.139	0.201
%ΔU.S. Soybean Stock	0.007	0.205	-0.476	1.13
%ΔFX	0.0086	0.191	-0.52	0.884

Notes. Sample period is 01/01/2005-12/01/2013 and total number of observations is 108. Returns are

calculated as $r_t = 100 \times (\ln F_t - \ln F_{t-1})$, where F_t is monthly settlement price of the futures contract on month t .

Table2. Augmented Dickey-Fuller Unit Root Test

Variable	τ	p-value
Futures Prices		
F_nonGM	-1.49	0.541
F_GM	-1.9	0.334
Log of Futures Prices		
Ln F_nonGM	-1.51	0.5271
Ln F_GM	-1.91	0.3265
Futures Returns		
R_nonGM	-6.12	<0.0001
R_GM	-7.69	<0.0001

Notes. The τ statistics and their p-values are presented for single-mean Augmented Dickey-Fuller unit root

test with one lag. GM and nonGM refer to GM soybean and non-GM soybean respectively. Futures

returns are calculated as $r_t = 100 \times (\ln F_t - \ln F_{t-1})$.

Table 3. DCC model results for non-GM and GM soybean futures

Mean Eq.	Non_GM	GM
Constant	-0.008 (0.983)	-0.12 (0.722)
Rt-1	0.037 (0)	0.032 (0.001)
Variance Eq.	Var(Non_GM)	Var(GM)
Constant	2.006 (0.001)	2.199 (0.000)
ARCH(1)	0.313 (0.002)	0.213 (0.045)
GARCH(1)	0.224 (0.013)	0.213 (0.072)
Lag_Gmreturn	0.002 (0.969)	
Lag_NonGMreturn		0.132 (0.000)
Crisis	1.852 (0.005)	2.952 (0.000)
FX	0.533 (0.768)	-3.168 (0.160)
IPI	-7.670 (0.359)	-8.150 (0.344)
Non_GMVol	1.092 (0.000)	1.051 (0.000)
GMVol	0.097 (0.070)	0.076 (0.040)
Stock/use	4.749 (0.001)	5.281 (0.042)
Production	-9.883 (0.148)	-20.223 (0.001)
Import	-3.284 (0.005)	-2.300 (0.002)
Oil	3.034 (0.174)	-0.105 (0.967)
planting	-1.154 (0.767)	-0.638 (0.231)
growing	-1.550 (0.029)	-1.181 (0.007)
harvesting	0.026 (0.968)	0.309 (0.568)



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AGRICULTURE IN AN INTERCONNECTED WORLD

DCC(1)	0.261	
	(0.073)	
DCC(2)	0.780	
	(0.000)	
LLF	-491.142	
LR	184.768	
	(0.000)	
Lyung-Box Q	44.612	54.346
	(0.097)	(0.045)

Note. The estimated coefficients on each term in the equation and their p-values are presented. LLf refers to loglikelihood function value. Likelihood ratio (LR) test statistics and its p-value for the null hypothesis of no exogenous variables in variance equations are given. Lyung-Box Q statistics and their p-value for the test of independence of the model residuals are presented.

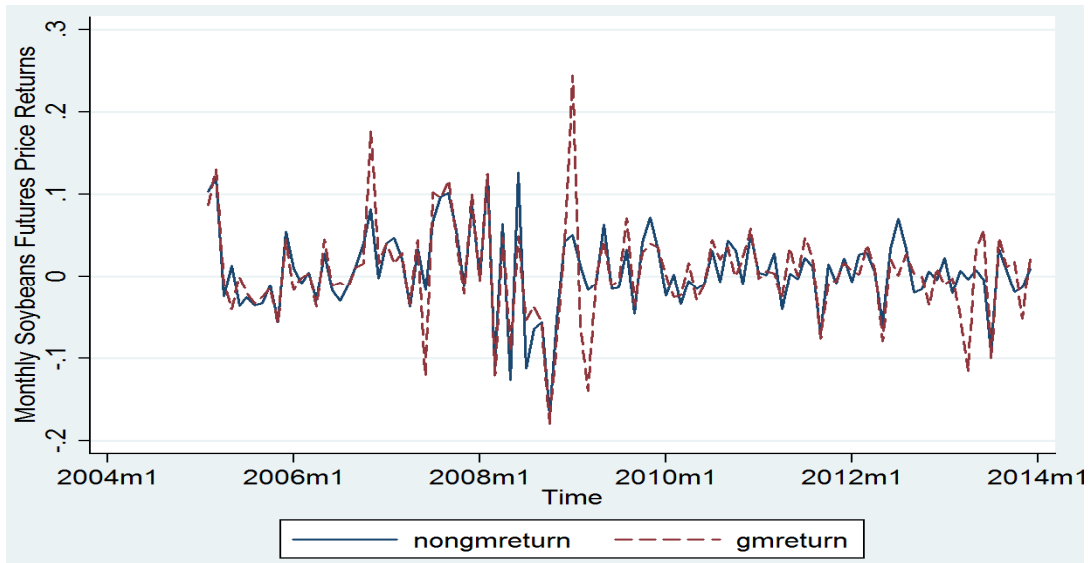


Figure 1 Monthly Non-GM and GM Soybean Price Returns
Source: DATASTREAM

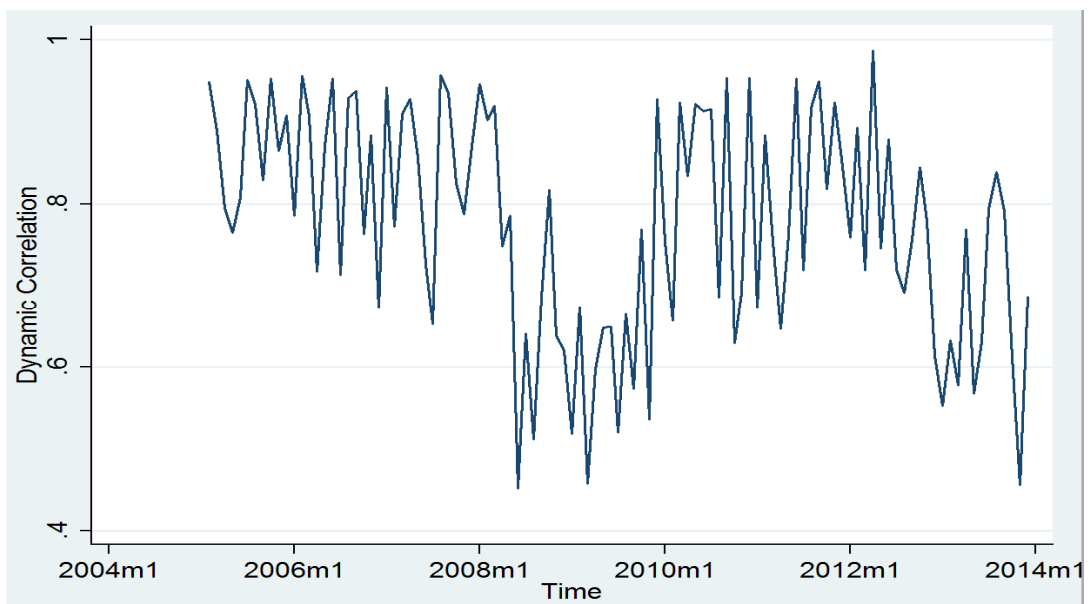


Figure 2 The estimated dynamic correlation coefficients between soybeans markets

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