SPILLOVER EFFECTS FROM SWAP DEALERS AND INDEX TRADERS ON AGRICULTURAL COMMODITY FUTURES, A BEKK-MGARCH APPROACH

A Thesis

by

FEI SHEN

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	Yu Zhang
Committee Members,	David J. Leatham
	Ximing, Wu
Head of Department,	David J. Leatham

December 2020

Major Subject: Agricultural Economics

ABSTRACT

The food market is suffering from the COVID-19 Pandemic and the Locust Crisis in 2020. The price of agricultural products is potentially under a high risk both in the spot market and futures market. We examine the effects from the two main participants, index traders and swap dealers, on futures returns and volatility for corn, soybeans, wheat, and live cattle. Multivariate generalized autoregressive conditional heteroscedasticity models are applied in the research with the weekly data from 2010 to 2020. We discuss the spillovers as well. The main finding is that the own past volatility significantly affects all the tested commodities' current volatility. A positive effect is observed between the past shock and the current volatility for all the tested commodities. The spillovers from the past volatility and innovation to the current volatility are observed in some bivariate models. Contemporaneous effects of index traders and swap dealers on the own returns are found in wheat and soybeans, and a lagged effect is found in live cattle. The index traders' trading is positively related to their own current volatility for corn and live cattle. The spillovers on the volatility across the commodities based on the index trading are very limited. The impact from the swap dealers trading on the own current volatility is found in corn, soybeans, and live cattle. The spillovers on the volatility based on the swap dealers' trading are limited to observe.

Keywords: Index traders, swap dealers, spillovers, BEKK, futures.

DEDICATION

I humbly dedicate this thesis to my loving parents, my wife, my grandma and my son for their endless guidance and support.

ACKNOWLEDGMENTS

Foremost, I would like to express my sincere gratitude to my committee chair, Professor Zhang, Yu, for my study and research's continuous support for her patience, motivation, enthusiasm, and immense knowledge. Her guidance helped me have a better view of theoretical knowledge. She provides a lot of primary suggestions on data selection and processing.

Besides, I would like to thank the rest of my committee members, professor Leatham, David J., and Professor Wu, Ximing, for their insightful comments.

Last but not least, I would like to acknowledge with gratitude the support, and love of my family - my parents Zhou, Musheng, and Shen, Xinqun; my wife Cheng, Jing; my son Shen, Shire who are born in that special year. They all kept me going, and this thesis would not have been possible without them.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supported by a thesis committee consisting of Professor Zhang, Yu; Professor Leatham, David J.; and Professor Wu, Ximing of the Department of Agricultural Economics.

All other work conducted for the thesis was completed by the student independently.

Funding Sources

I did not receive any additional funding.

NOMENCLATURE

ADF-TEST	Augmented Dickey-Fuller test
ARIMA	Autoregressive Integrated Moving Average
BEKK-GARCH	Baba, Engle, Kraft and kroner Multivariate Generalized Autoregressive conditional heteroskedasticity
CBOT	Chicago Board of Trade
CFTC	Commodity Futures Trading Commission
CME	Chicago Mercantile Exchange
CIT	Commodity Index Trader
CPO	Commodity Pool Operator
CTA	Commodity Trading Advisor
ECT	Error Correction Term
EMH	Efficient Market Hypothesis
NLPI	Net Long Position of Index Traders
NLPS	Net Long Position of Swap Dealers
OTC MARKET	Over-The-Counter Market
PP-TEST	Phillips-Perron test
USTR	The United States Trade Representative
VAR	Vector Autoregression
VECM	Vector Error Correction Model
ZA-TEST	Zivot-Andrews Test

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

TABLE Page

1. INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction and Background

When looking at the worldwide food price index in recent decades, it is easy to find that the food price fluctuates a lot every decade, like the periods of 1994-1996, 2006-2008, and 2011-2013. The rest of the years in these decades looks stabilized. There are a lot of researches focus on the reasons why the price hikes or price drops. Von Braun(2007), Dewbre et al. (2008), and Krugman (2011) attribute the price spike into the high demand from the developing countries after 2000, especially in China and India. Hochman et al. (2014) developed an empirical model that presents some other reasons like economic growth, biofuel expansion, exchange rate fluctuations, and energy price inflation. Malesios et al. (2020) argue that climate change increases the chance of extreme weather events, leading to significant food production losses. The local government will formulate policies to restrict the import and export of agricultural commodities to fulfill the domestic market first. In general, the research above discusses the reasons for agricultural commodity price fluctuation from the supply, demand, and transportation sides. All these reasons will undoubtedly affect the price of food.

The spot market and futures market for agricultural commodities largely determine the price of products we purchase in daily life. Accordingly, the trading behavior may affect the products' prices through the spot market and futures market as if the stock trading will affect the company's valuation. The futures market has two leading players traditionally, one is the hedgers, and another is the speculators. In the agricultural field, hedgers are mainly composed of farmers. They buy or sell the futures contract to cover the risk of price fluctuation or crisis to stabilize their income with certain products. The speculators are mostly like stock investors who want to benefit from the price change from the original date to the contract's expiry date. Lauge Stetting(1964) discusses that there are "small" and "big" speculators in the futures market. The "small" speculators prefer to invest in the long-run and predominantly in late dates of delivery, their investment based on the fundamental analysis on supply and demand conditions, which are more likely links to the spot market. The "big" speculators have more interest in the nearby dates of delivery, and they always have superior knowledge or information about the stocks and ownership conditions in the relevant markets.

It is easy to find the connection between the spot market and the futures market. In definition, the futures market kind of a preview of the spot market. However, the argument about the causality between spot markets and futures markets has never stopped. Yang and Leatham(1999) indicate that the futures markets prefer to collect more information than the cash markets to find the equilibrium price. The futures market will generally lead the price discovery process after analyzing the wheat data from the Chicago Board of Trade, Kansas City Board of Trade, and Minneapolis Grain Exchange. Garbade and Silber(1983) find similar evidence that the futures markets dominate cash markets. The evidence in wheat, corn, and orange juice illustrates that about 75% of new price-related information found in futures markets first, and then flow to the cash markets. In contrast, there is about 25% information will flow to the cash markets first. There are some researches indicates the spot markets may lead to the futures market. Shyy et al. (1996) state the findings that the spot markets significantly lead the futures markets, and the result may be primarily due to asynchronous market trading or different trading mechanisms.

In recent decades, many research pays more attention to price changes in a single market due to the research methodology improvement. This paper is interested in the futures markets for agricultural commodities like wheat, corn, soybean, and live cattle. We can see from figure 1.1 that the food price index in nominal at real data experience dramatically change during every decade, like 1994-1996, 2006-2008, 2011-2013. Due to the mainstream concept that futures markets lead the spot markets in academia, studies are more likely to explore futures markets' secrets. The significant factors are returns and volatility, which most players in this market focus on. Like the players in other financial markets, people want to increase the returns and lower the risk when they invest in the futures market. Based on "CME Group Reports 2019 Annual Volume and Monthly Market Statistics", the average daily volume traded through "CME Globex" enjoy a significant

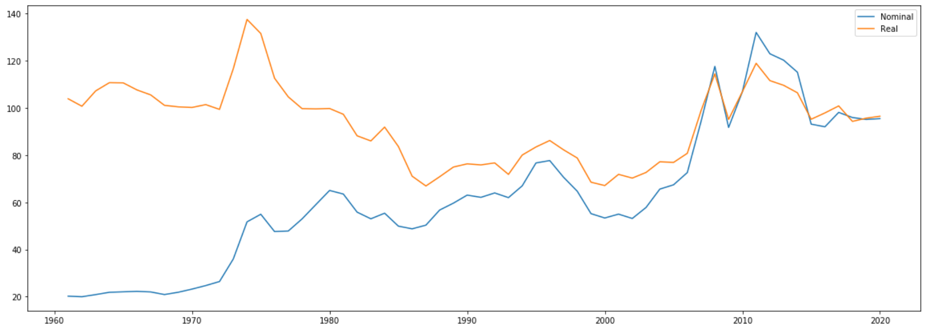

Figure 1.1: Food and Agricultural Organization(FAO) Food Price Index (2014-2016=100 for nominal index)

increasing trend. We can see the result of figure 1.2, which is the data related to agricultural commodity contracts traded. All the evidence shows that the market has been expanding. In the meanwhile, economic and financial analysis becomes more valuable and effective for the futures market. There is various research that has been done to discuss the price prediction of the futures market. Ouyang, Wei, and Wu(2019) apply LSTNet to predict the agricultural commodity futures prices. The volatility of the futures market is also a question worthy of in-depth study. Beckmann and Czudaj(2014) present volatility transmission in the agricultural futures market by a GARCH-in-mean VAR model. The cointegration study on the futures market's returns and volatility also be a key topic when discussing the long-run effect.

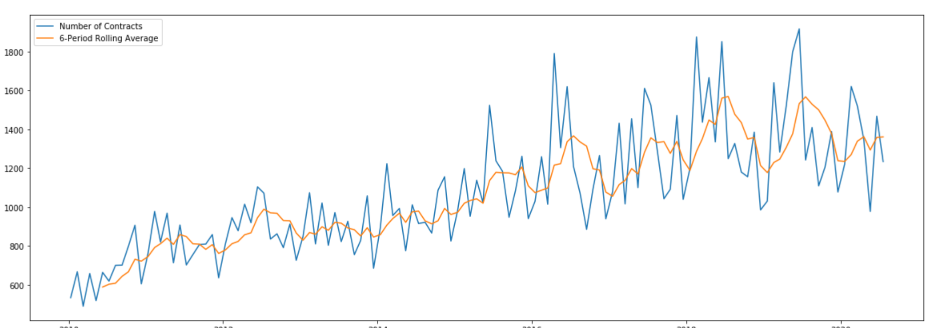

Figure 1.2: Average Daily Trades by CME Globex

The spillover effect initially describes an effective transmission from one market to other markets. It is always used to study the relationship between the spot market, futures market, and currency market. The majority of current literature adopts the spillover effect on the spot market and futures market to find the price discovery function and the price transmission between these two markets for the agricultural market. This paper will adopt the spillover effect inside the futures market for the agricultural commodity in returns and volatility with a VAR-BEKK-GARCH model. An in-depth discussion about the methodology will be present in the methodology design section. This paper will apply the VAR-BEKK-GARCH model to discuss the volatility and returns spillovers crossing each factor. This paper aims to give some ideas about the transmission between the returns and volatility in the futures market across commodities, like corn, soybean, wheat, and live cattle.

Dai, Xiong, and Zhou(2020) give an idea that the global economic policy uncertainty(GEPU) has a significant impact on predicting the crude oil futures volatility from a two-factor GARCH-MIDAS model. The US-China trade negotiations have an essential impact on global economic activities, especially for the domestic agricultural commodity market in the United States when China redesign the plan of importing U.S. agricultural commodities. This paper will present a brief discussion about the impact of US-China trade negotiations on the agricultural commodity's futures market. It will be a new contribution to the academic area.

This paper uses the weekly data on the swap dealers and money managers' net long position reported by CFTC, which we measure as a factor of influence from the OTC market and Index traders on the futures returns. We consider the corn, wheat, soybeans as storable commodities and live-cattle as non-storable commodities. The main object we are looking at is the potential spillovers on the futures returns and volatility from the swap dealers' and money managers' net long position change contemporaneously. Lags impacts also will be considered. Based on the results, this paper will provide some suggestions to the other participants in the futures market, like farmer, merchant, and processor, to help them to estimate a better hedging strategy.

We want to achieve another objective that discusses the spillovers during the COVID-19 pandemic and US-China trade negotiation. We will add the dummy at the significant dates and apply them to our model to find the results.

This paper is structured as following steps. Chapter 1 gives introduction and literature reviews. Chapter 2 will propose data and methodology design. Chapter 3 reports the empirical results and interprets the coefficients we have. Chapter 4 provides concluding comments and suggestions to related parties.

1.2 Literature Review

The first modern futures exchange began in 1710 in Japan. The futures market's primary function is to provide producers to avoid the risks of price fluctuations in the spot market. Meanwhile, the speculators who want to be a risk-taker of the price fluctuations in the spot market engage the futures market takes the long or the short position of the contract. When the market matures, more and more money managers or investor agencies want to benefit from the futures market. They believe they have more information and stronger professional background to do the fundamental analysis of commodities' supply and demand equilibrium. While funds continue to be injected into the futures market, large transactions begin to affect the futures market's price and price fluctuation. Gilbert and Pfuderer(2014) use both the Granger-causality and instrumental variables(IV) methods to examine the impact on the index trading on the U.S. grains and oilseeds futures markets. They present strong evidence that the index positions change could help to predict the aggregate commodity price indices.

Previous research on the futures market for the agricultural commodity can be summarized into a couple of topics. The most direct topic is to predict the futures price. Malliaris and Urrutia(1998) indicate the cointegrated relationship between the futures price and volume in the long-run. The result fails to explain the Weak Efficiency Market Hypothesis(WEMH) that the past price and volume data have no relationship with the following futures price. The current popular methodology in predicting futures price is Long- and Short- Term Time-series Network(LSTNet). The traditional approaches such as Auto-Regressive Integrated Moving Average(ARIMA) and Vector Auto-Regression(VAR) may fail to explain the mixture of long- and short- term information.

Ouyang, Wei, and Wu(2019) show that LSTNet significantly improves the forecasting on the agricultural commodity futures price by applying the cotton, sugar, bean, and soybean futures data from Zhengzhou Commodity Exchange(CZC). Another popular topic is to explore the relationship between the spot market and futures market, including the price discovery function, the dominance, and the volatility transmission. Chauhan, Singh, and Arora(2013) conclude that the futures markets effectively serve the price discovery function in the spot market by an information transmission from the futures markets to the spot markets for the commodity of gaur seed and chana in Indian markets. Mallikarjunappa(2013) provides a new idea that the futures returns are influenced by the first lag spot returns, but not the second lag. An unexpected finding is that the lags itself do not affect the futures returns. The third topic focuses on the participants' behavior, especially for the index trader who always like to diversify the portfolio and do large volume transactions. In the overall futures markets, most research participants prefer to use index futures as a key factor in evaluating the influence of index trading. Chen(2014) shows the index futures trading like the S&P 500, Nikkei 225, and Nasdaq 100 impact the spot volatility. Power and Turvey(2011) divide the commodity into the storable commodity and the non-storable commodity. They introduce that the large index trader volume will increase the price volatility for the storable commodity futures. However, the impact on the non-storable commodity futures is weak. Yang, Bessler, and Fung(2004) have a similar result that the futures prices and open interest have a long-run relationship for the storable agricultural commodity(corn, wheat, and soybean), but not for the non-storable agricultural commodity(live cattle). In contrast, Gilbert(2012) has the result that there is minimal evidence to show the lagged index trading affects the volatility of the futures price in corn, soybean oil, and soybeans by univariate GARCH-X model. Hamilton and Wu(2014) find significant evidence that increasing futures investors' activity will change the risk premium on the oil futures market. The story is different in Hamilton and Wu(2015). They demonstrate no relation between the 12 agricultural commodities' futures price and the index-fund investment behavior.

A primary topic discussed in this paper is the spillover effect. The spillover effect is discussed in many academic fields. Sarah et al. (2020) indicate the spillover effects of collective action in global supply chains. Herwartz and Saucedo(2020) present food-oil volatility spillovers. Bechky(2020) evaluates spillovers from technological change in forensic science. The spillover effect discussion also very popular in economic and financial research. Zhang et al. (2008) find the US dollar exchange rate's spillover effect on the oil price. Chang and Lee(2020) estimate a multichain Markov switching dynamic conditional correlation ARCH model shows an asymmetric spillover effect from the futures market to the spot market in crude oil.

There is minimal literature on the spillover effects in agricultural futures markets. The literature about the US futures market is even less. Booth(1998) develops the Error Correction Model and Granger-causality on the US and Canadian wheat futures. The finding is that the wheat futures prices in Winnipeg Commodities Exchange(WCE) and Chicago Board of Trade(CBT) are cointegrated, even the WCE provides feed wheat and CBT provides milling wheat. Another result is that the CBT contract leads the WCE contract with no feedback, which means the spillovers are one-way. Beckmann and Czudaj estimate GARCH-in-mean VAR models prove there exist short-run volatility spillovers in agricultural futures markets. Hernandez, Ibarra, and Trupkin(2014) follow an MGARCH approach, indicating that agricultural markets are highly interrelated, own- and cross- volatility spillovers among most exchanges. CBOT plays a dominant role in spillovers over the other futures markets. Lopez and Dawson(2017) use bivariate MGARCH models to examine the spillovers on the corn, soybeans, and wheat futures from 2006 to 2014. They announce the results that the spillovers in returns are not significant for their past returns. They prove the opposite result in the volatility part.

In summary, a VAR model is always used to evaluate the linkage of the futures return. A multivariate-GARCH model is a good choice in discussing the volatility in the previous research. Index futures and reported fund-investor trading data are used to measure the index trading, which is interested in exploring the spillovers crossing commodities or markets.

2. DATA AND METHODOLOGY

2.1 Data Description

2.1.1 Data Collection and Explanation

This paper collects two data types. The first data type is the weekly futures price of the chosen commodities from 01/12/2010 to 07/28/2020. There are a total of 551 weekly futures price data for each commodity, including corn, wheat, soybeans from the Chicago Board of Trade (CBOT), and live cattle from the Chicago Mercantile Exchange (CME). The corn, wheat, and soybeans are three agricultural benchmark commodities, and all these commodities are classified in storable products. The live cattle is classified in non-storable products. The corn, soybeans, wheat, and live cattle's futures contracts are expiring on the 14th of the expiry month or the prior trading day if the 14th is a holiday or a weekend. Refer to the former literature, Sanjuán-López, Dawson (2017) and Gilbert, and pfuderer (2014), we roll over the prices on the first trading day of each month and assign weekly price data for the same nearest expired contract.

The second data type is the weekly trading volume from swap dealers and money managers, which are reported from Commitments of Traders Reports by Commodity Futures Trading Commission (CFTC). The Commitments of Traders Reports are reported every Tuesday or the first workday before Tuesday. To facilitate the integration of data, we revised all the data to Tuesday each week. The Commitments of Traders Reports list the trading volume information, including long position, short position, and spreading position, in open interest, producer/merchant users, swap dealers, money manager, and other reportable subjects. A swap dealer is an entity, and they could be speculative traders, like hedge funds or traditional commercial traders who want to manage the risk of physical commodity trading. The CFTC defines the money manager as a registered commodity trading advisor (CTA), registered commodity pool operator (CPO), or an unregistered fund identified by CFTC. The money manager engages in futures trading on behalf of clients. The swap dealers and money managers are two main participants in the market, and the aggregate long position proportion in the open interest are represented in figure 2.1. The average aggregate proportion above 40% for soybeans and corn, and 60% for wheat and live cattle. A large position change by the index traders and swap dealers should affect the futures price for these commodities. The money managers are considered as index traders in the previous literature, like Hamilton, Wu (2015), Sanjuán-López, Dawson (2017), and Gilbert and pfuderer (2014). The swap dealers' main objective is to offset their risk in the over-the-counter (OTC) market through the futures market, regardless of whether their counter-party is a speculator or not in the OTC market. We apply the data related to swap dealers to introduce some impacts on the futures market from the OTC market. The money managers' data will be used to discuss the relationship between the futures return and the index traders' behavior.

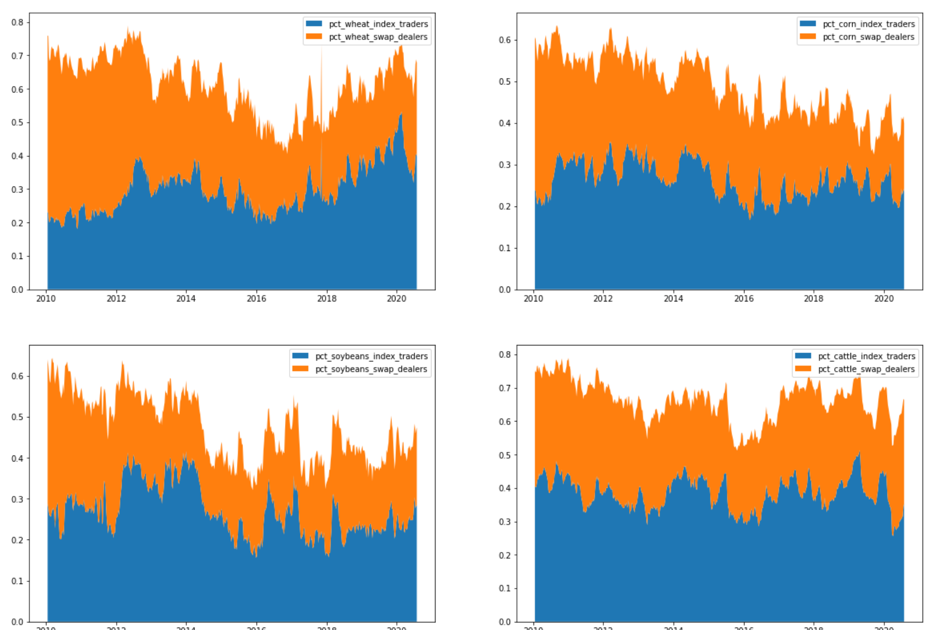

Figure 2.1: Long Position Proportion of Index Traders and Swap Dealers

2.1.2 Data Preprocessing

This paper defines the p_t as the natural logarithm of weekly futures price at time t. The overview of the logarithm price for each commodity is illustrated in figure 2.2. We also define futures percentage returns as $r_t = (p_t - p_{t-1}) * 100$, and the shape of the percentage returns be presented in figure 2.2 as well.

The paper picks the index traders' and the swap dealers' position data first. We define the net long position of index traders and swap dealers as equation 2.1 and equation 2.2.

$$NLPI_t = LPI_t - SPI_t \tag{2.1}$$

$$NLPS_t = LPS_t - SPS_t \tag{2.2}$$

where LPI and SPI are the long and short positions of index traders reported, and LPS and SPS are the long and short positions of swap dealers reported. Following Sanders, Irwin(2015), and Sanjuán-López, Dawson(2017), we measure the net long position percentage change as equation 2.3 and equation 2.4. Both the equations 2.3 and 2.4 have a disadvantage when the net position in time t over time t-1 is negative. To avoid the error during the data processing, we change the equation into equation 2.5 to make the data more sensible.

$$\nabla NLPI_t = ln[\frac{LPI_t - SPI_t}{LPI_{t-1} - SPI_{t-1}}] * 100 \tag{2.3}$$

$$\nabla NLPS_t = ln[\frac{LPS_t - SPS_t}{LPS_{t-1} - SPS_{t-1}}] * 100 \tag{2.4}$$

$$\nabla NLPI/S_t = -ln[-(\frac{LPI/S_t - SPI/S_t}{LPI/S_{t-1} - SPI/S_{t-1}})] * 100 \tag{2.5}$$

Figure 2.2 illustrates the logarithm futures price, percentage returns, and net long position percentage change for each commodity. The paper will do in-depth processing of the data in the model if necessary.

2.2 Methodology Design

The general procedure follows three steps. Firstly, we do the fundamental analysis of the futures price, futures percentage returns, $\nabla NLPI$ and $\nabla NLPS$. Then, we test for stationarity, serial dependence, and ARCH effects. Secondly, We set up the mean equation by VAR or VECM.

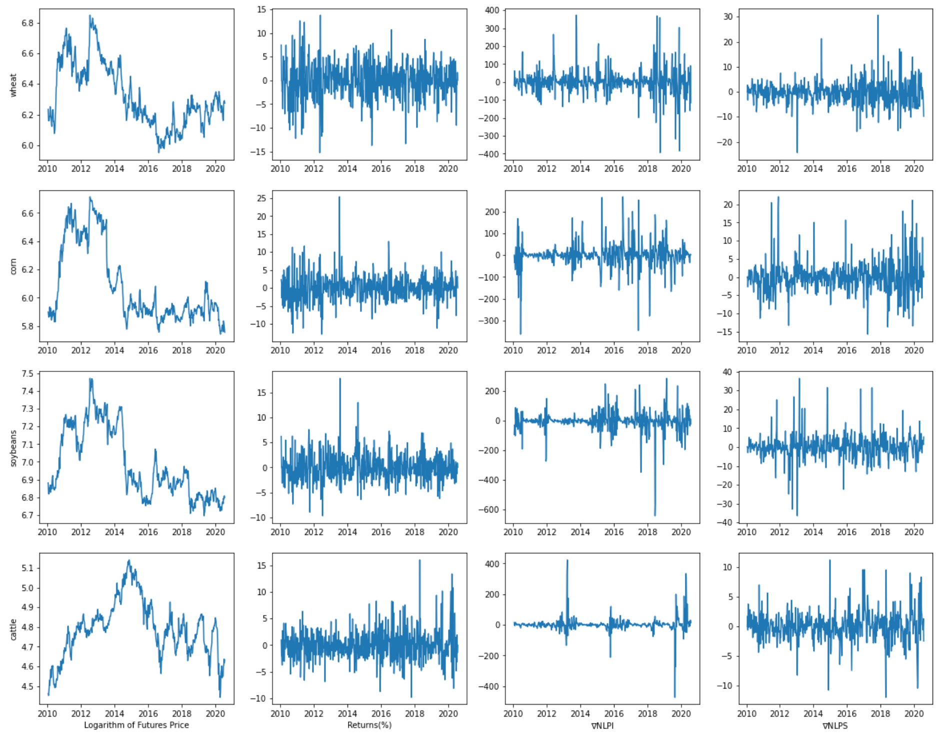

Figure 2.2: Overview of Data

The final step is setting the BEKK-MGARCH model to figure out the results that we are interested in.

2.2.1 Preliminary Analysis of Data

The paper defines the returns as the logarithm difference of the price in the data preprocessing. We test serial dependence of the squared returns by McLeod and Li (1983) test. The Ljung-Box Q-statistics of Mcleod-Li test is given by:

$$Q = N(N+2)\sum_{k=1}^{L}\frac{\hat{\rho}_k^2(\epsilon^2)}{N-k} \tag{2.6}$$

where N is the sample size, L is the number of lags, ϵ is the residual sequence, and $\hat{\rho}$ is the sample autocorrelation of residual at lag k. The null hypothesis is that there is no serial correlation in the data. The statistic Q is asymptotically $\chi^2(L)$ distributed.

We test the ARCH effect by Engle's (1982) Autoregressive Conditional Heteroscedasticity-

Lagrange Multiplier (ARCH-LM) test. The Phillips and Perron (PP) (1988) test and the Augmented Dickey-Fuller (ADF) test are adopted to test for unit roots.

2.2.2 Mean Equation

We adopt the bivariate model to interpret the spillovers between the returns by adding the volume data from index traders and swap dealers. To avoid the joint autocorrelation, a bivariate VAR model is used as a mean equation for our next step modeling. A Vector Autoregressive (VAR(p)) model is estimated as:

$$r_t = \mu_0 + \sum_{i=1}^{p} \beta_i \cdot r_{t-1} + \varepsilon_t \tag{2.7}$$

where r_t and r_{t-1} are 2×1 vectors of returns in time period t and t-1. β_i is a 2×2 matrices of coefficients, and ε_t is a 2×1 vector error term in the model. The β_i interprets the spillovers in returns in the mean equation.

Malliaris and Urrutia (1996) indicate evidence that agricultural commodity futures prices are cointegrated. A VECM is preferred if the price data are cointegrated rather than the VAR model. Engle-Granger (1987) two-step approach is used to test for cointegration between the futures prices. The Engle-Granger two-step approach begins with the stationary test of each futures price through the PP test and ADF test. We take the first difference if the price data is non-stationary. Data is defined by I(1) if the first difference is stationary. We estimate the OLS for every two variables and do the ADF test for the errors of each model. After we determine the cointegration relationship between the futures logarithm prices, we will decide to use the VECM or VAR to our bivariate model. The VECM model is defined as:

$$r_t = \mu_0 + \alpha ECT_{t-1} + \sum_{i=1}^{p} \beta_i \cdot r_{t-1} + \varepsilon_t \tag{2.8}$$

where ECT_{t-1} is a lagged error-correction term represents the cointegrated vector of futures prices. α is a 2×1 vector coefficients of the error-correction term, which represents the long-run adjustment.

Gilbert and pfuderer (2014) find that the contemporaneous causal link from the commodity index traders (CIT) trades to futures returns. As the description of Efficient Markets Hypothesis[1] (EMH) and Market microstructure theory, the past and contemporaneous trading behavior also can be an impact on the current futures price. Let the f_t be the futures price at time t, η_t be the public information in time t, and η_{t+i} be the aggregate information including the trades made in the current period and be published in time $t+i$ where $0 < i < 1$. The EMH implies $E(f_{t+1}|\eta_t) = f_t$, and the market microstructure theory implies $E(f_{t+1}|\eta_{t+i}) = f_t$. We add the trade information from the index traders and the swap dealers into our mean equation. The VAR(p) and VECM(p) are revised as equations 2.9 and 2.10. Besides the impact from the swap dealers and index traders' trading behavior contemporaneously, there may be some omitted variables that need to be specified. This is a general criticisms mentioned in Gilbert and pfuderer (2014) to the Granger-causality test as well.

Gilbert and pfuderer (2014) provide a solution that uses lagged returns of related commodities' returns and the traders' position change as instruments to test the causality. This paper will follow the same steps against the omitted variable problem. We will add the lagged returns of the related futures return and the lagged net long position change both in swap dealers and index traders. All the variables are displayed in equations 2.9 and 2.10.

$$r_t = \mu_0 + \sum_{i=1}^{p} \beta_i \cdot r_{t-1} + \sum_{j=0}^{1} \theta_i \cdot Z_{t-j} + \varepsilon_t \tag{2.9}$$

$$r_t = \mu_0 + \alpha ECT_{t-1} + \sum_{i=1}^{p} \beta_i \cdot r_{t-1} + \sum_{j=0}^{1} \theta_i \cdot Z_{t-j} + \varepsilon_t \tag{2.10}$$

where Z can be the net long position percentage change for index traders or swap dealers.

[1]The Efficient-market Hypothesis states that the price reflects all the available information, which indicate that a risk-adjusted basis could not "beat the market" for the reason that the market only reacts to new information.

2.2.3 BEKK-MGARCH

Based on the mean equation estimated, we introduce the BEKK-MGARCH (Baba, Engle, Kraft and Kroner Multivariate Generalized Autoregressive Conditional Heteroskedasticity) model[2] in the final step to find out the spillovers in volatility across the futures.[3][4]

The conditional covariance is specified by bivariate BEKK based on the mean equation we have. We present the variance-covariance matrix as:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2.11}$$

where C is a 2×2 lower triangular matrix. A is a 2×2 matrix represents the impact from the past residuals to the current volatility. It can be understood as the information from the market at the last period affect the volatility in the current period, also can be treated as the ARCH effect[5]. B is a 2×2 matrix measures the impact from the past volatility to the current volatility. We have the $\sigma_t \sim WN(0,1)$ as the standardized error, $\sigma_t = Q_t\varepsilon_t$, and $H_t^{-1} = Q_t^{'} \cdot Q_t$.

Rewriting the equation 2.14 in a matrix way by substituting the corn-soybeans model provides

[2]Engle and Kroner(1995) proposed the BEKK model to ensure the condition of positive-definite conditional-variance matrix in the optimization process.

[3]There are various of models to explore the volatility relationship in different markets, the dynamic conditional correlation (DCC) and BEKK are two most widely used models to discuss the conditional covariances and correlations. Due to the result from Caporin and McAleer (2012), the DCC is better to forecast conditional correlation, and the BEKK is more favored in the conditional covariance.

[4]Hernandez et al. (2013) indicate that the BEKK-MGARCH model is better suited to explain the volatility transmission across exchanges to compare with DCC-MGARCH model.

[5]The ARCH concerns the time-varying heteroskedasticity.

a clearer explanation of the conditional covariances.

$$\begin{aligned}
\begin{bmatrix} h_{cc,t} & hcs,t \\ hsc,t & hss,t \end{bmatrix} &= \begin{bmatrix} c_{cc} & 0 \\ c_{sc} & c_{ss} \end{bmatrix} \cdot \begin{bmatrix} c_{cc} & c_{sc} \\ 0 & c_{ss} \end{bmatrix} \\
&+ \begin{bmatrix} a_{cc} & a_{sc} \\ a_{cs} & a_{ss} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_{c,t-1} \\ \varepsilon_{s,t-1} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_{c,t-1} & \varepsilon_{s,t-1} \end{bmatrix} \cdot \begin{bmatrix} a_{cc} & a_{cs} \\ a_{sc} & a_{ss} \end{bmatrix} \\
&+ \begin{bmatrix} b_{cc} & b_{sc} \\ b_{cs} & b_{ss} \end{bmatrix} \cdot \begin{bmatrix} h_{cc,t-1} & hcs,t-1 \\ hsc,t-1 & hss,t-1 \end{bmatrix} \cdot \begin{bmatrix} b_{cc} & b_{cs} \\ b_{sc} & b_{ss} \end{bmatrix}
\end{aligned} \tag{2.12}$$

The variance and covariance for corn and soybeans in time t are presented in equation **??** as $h_{cc,t}, h_{ss,t}$ and $h_{cs,t}, h_{sc,t}$. To interpret the coefficients, we list the full variance equation of corn ($h_{cc,t}$) in the corn-soybeans model as:

$$\begin{aligned}
h_{cc,t} = c_{cc}^2 + a_{cc}^2\varepsilon_{c,t-1}^2 + 2a_{cc}a_{sc}\varepsilon_{c,t-1}\varepsilon_{s,t-1} + a_{sc}^2\varepsilon_{s,t-1}^2 \\
+ b_{cc}^2 h_{cc,t-1} + 2b_{cc}b_{sc}h_{cs,t-1} + b_{sc}^2 h_{ss,t-1}
\end{aligned} \tag{2.13}$$

where a_{cc}^2 measures the impact from the first-order lag innovations of corn, and b_{cc}^2 measures the influence from the first-order lag volatility on the conditional volatility of corn futures return. The direct and indirect spillovers across the commodities are represented by A and B, such as the direct effect on the conditional volatility of corn futures returns from the past innovation of soybeans futures returns represented by a_{sc}^2, the indirect effect represented by $a_{cc} \cdot a_{sc}$. The b_{sc}^2 measures the spillovers from the soybeans futures return's conditional volatility to the conditional volatility of corn futures returns.

As the same as the mean equation in 2.2.3, we expect to add the trading information into the model. Moschini and Myers (2002) provide a way to modify the BEKK by adding the exogenous variables into the C in the equation. Thieu and Le (2016) add the exogenous variables straightly into the equation with a lower triangle coefficient matrix E. Following this procedure, modify the equation 2.14 to:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + EZ_tZ'_tE' \tag{2.14}$$

Z measure the same variables with the mean equation in equations 2.9 and 2.10. The models are estimated by the BFGS (Broyden, Fletcher, Goldfarb, and Shanno) algorithm. Finally, we test the ARCH effect to make sure the model is fully specified and do not have the ARCH effect anymore.

3. EMPIRICAL RESULTS

3.1 Basic Statistical Descriptions of Data

Weekly futures prices, which are reported in every Tuesday from 01/12/2010 to 07/28/2020 with 551 observations used in our model. The report of index traders and swap dealers data are released each Friday describes the reports from the last Tuesday to the current Tuesday. We ignore the time gaps for the reason that the current trading behavior could be observed by the participants to some extent in the market, which will affect their investment. Basic statistical descriptions of our futures data are listed in table 3.1, and position data are reported in table 3.2.

In table 3.1, all the commodities' logarithm prices' ADF and PP statistics are not significant, which means the null hypothesis can not be rejected. A unit root existence can not be rejected for each time series, which means we can not say the time series of the logarithm prices are stationary. A first difference may be considered to make the series stationary. The first difference of logarithm price is introduced by the logarithm returns. $ln(p_t) - ln(p_{t-1}) = ln\frac{p_t}{p_{t-1}}$.

According to the Jarque-Bera statistic, the variables are non-normal distributed. Positive skewness indicates a longer tail on the right for the logarithm returns of corn, soybeans, and live cattle. The logarithm returns of wheat have a longer tail on left. The kurtosis for corn, soybeans, and live cattle are a higher than 3, which indicates a higher peak and fatter tail distribution. We have the means for all commodities are insignificantly different from zero, which are fulfilled for our expectations. McLeod Li test is taken on the futures logarithm returns for each commodity, and the results show serial correlations for 5 and 10 lags. ARCH-LM test shows statistics significant up to 5 lags for each commodity, which tells the ARCH effects.

All of the ADF-test, PP-test, and ZA-test reject the unit-roots for all the logarithm returns of each futures, which means all the series are stationary.

The ZA-test also gives structural break points, which will be listed in the mean equation's section. Table 3.2 shows all stationary series of $\nabla NLPI$ and $\nabla NLPS$ as we expected.

Table 3.1: Basic statistical description and univariate tests

	corn	wheat	soybeans	live cattle
Logarithm prices of each futures				
Mean	6.087	6.324	6.988	4.790
Standard Deviation	0.274	0.209	0.196	0.143
Minimum	5.741	5.951	6.695	4.442
Maximum	6.715	6.850	7.472	5.141
Skewness	0.894	0.507	0.552	0.144
Excess Kurtosis	-0.741	-0.680	-1.056	-0.140
Augmented Dickey-Fuller	-1.537[0.77]	-2.518[0.36]	-2.333[0.44]	-2.073[0.55]
Phillips and Perron	-1.748[0.41]	-2.107[0.24]	-1.858[0.352]	-1.784[0.39]
Logarithm returns of each futures in percentage				
Returns(%)				
Mean	0.029	-0.007	0.015	-0.031
Standard Deviation	3.719	3.896	2.854	2.874
Minimum	-12.919	-15.244	-9.681	-9.836
Maximum	25.427	13.784	17.834	15.999
Skewness	0.570	-0.311	0.657	0.848
Excess Kurtosis	4.726	1.310	3.263	3.512
JB Statistic	531.79[0.00]***	45.383[0.00]***	271.04[0.00]***	343.06[0.00]***
$Q_{ML}(5)$	17.236[0.00]***	38.173[0.00]***	19.328[0.00]***	35.571[0.00]***
$Q_{ML}(10)$	21.342[0.01]**	67.365[0.00]***	22.559[0.01]***	45.573[0.00]***
ARCH(1)	12.837[0.00]***	1.956[0.16]	9.840[0.00]***	3.426[0.06]*
ARCH(5)	14.829[0.01]**	32.278[0.00]***	14.976[0.01]**	28.833[0.00]***
Augmented Dickey-Fuller	-10.086[0.00]***	-13.087[0.00]***	-23.527[0.00]***	-18.610[0.00]***
Phillips and Perron	-22.794[0.00]***	-23.038[0.00]***	-23.535[0.00]***	-25.205[0.00]***
Zivot and Andrews	-23.078[0.00]***	-23.063[0.00]***	-23.719[0.00]***	-25.418[0.00]***

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *. Q_{ML} are the test statistics of McLeod-Li test, and ARCH measures the test statistics of ARCH-LM test.
[c] ADF and PP test uses lag-order=8.

Table 3.2: Basic statistical description and univariate tests of the net long positions

	corn	wheat	soybeans	live cattle
$\nabla NLPI$				
Mean	-0.085	2.021	-4.128	2.126
Standard Deviation	57.555	69.394	73.024	50.632
Minimum	-362.898	-394.308	-643.090	-473.412
Maximum	268.235	373.040	287.969	423.341
Augmented Dickey-Fuller	-20.634[0.00]***	-15.066[0.00]***	-15.954[0.00]***	-9.504[0.00]***
Phillips and Perron	-20.584[0.00]***	-23.397[0.00]***	-16.962[0.00]***	-20.728[0.00]***
$\nabla NLPS$				
Returns(%)				
Mean	0.116	-0.135	0.000	-0.004
Standard Deviation	4.401	4.631	6.302	2.505
Minimum	-15.754	-24.361	-36.508	-11.948
Maximum	22.113	30.660	36.477	11.164
Augmented Dickey-Fuller	-14.859[0.00]***	-12.276[0.00]***	-21.575[0.00]***	-13.213[0.00]***
Phillips and Perron	-21.526[0.00]***	-23.138[0.00]***	-21.563[0.00]***	-18.669[0.00]***

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] ADF and PP test uses lag-order=8.

3.2 Mean Equation Establishment and Analysis

Table 3.1 shows the non-stationary of logarithm prices for each series, and the first difference of the logarithm prices are stationary. The result indicates that the logarithm prices are integrated of order 1, and we do the cointegration analysis to determine if the VECM is more appropriate to be the mean equation rather than the simple VAR model.

3.2.1 Engle-Granger Two-Step Cointegration Analysis

Bivariate OLS regression[1] is adopted between each variable. A Durbin-Waston test is used to test the independence of the residual series from the bivariate OLS regression. Based on the results from table 3.3, we can see that all the constant and the most variables are significant in the bivariate OLS models between every two commodities. The Durbin-Watson statistics are significant in all the models, which means the residuals series are not independent. The stationarity of residuals from each regression is tested by ADF-test without drift, and the results are listed in table 3.3 as well. Residuals from the corn-soybeans model, the corn-wheat model, the soybeans-wheat model, and the wheat-live cattle model are significant in 5% level, which means a rejection of unit-roots. Cointegration is confirmed between the corn-soybeans model, the corn-wheat model, and the soybeans-wheat model. However, it is rejected in the corn-live cattle model, the wheat-live cattle model and the soybeans-live cattle model. The cointegration indicates a long-run relationship between these futures logarithm prices. The second step is to establish the vector error correction model between the variables who are integrated, which will be introduced in 3.2.2.

3.2.2 Mean Equations with Trading Information applied

The mean equation model will be specified in this section. The bivariate VAR or VECM models will be established with trading information inside. The first lag of error correction terms are collected from the residual of the corn-soybeans model, the corn-wheat model, and the soybeans-wheat model. The trading information related to index traders and swap dealers in the current and first lag period will be added into the mean equation model to specify the spillovers of returns.

[1]Simple OLS regressions are not listed in the paper

Table 3.3: Cointegration analysis for logarithm futures prices

	corn-soybeans		corn-wheat		corn-live cattle	
	corn equation	soybeans equation	corn equation	wheat equation	corn equation	live cattle equation
OLS Estimators						
constant	-2.381[0.00]***	3.205[0.00]***	-1.238[0.00]***	2.234[0.00]***	5.824[0.00]***	4.697[0.00]***
corn	-	0.622[0.00]***	-	0.672[0.00]***	-	0.015[0.50]
soybeans	1.212[0.00]***	-	-	-	-	-
wheat	-	-	1.158[0.00]***	-	-	-
live cattle	-	-	-	-	0.055[0.5]	-
Durbin-Waston Statistic	0.081[0.00]***	0.084[0.00]***	0.104[0.00]***	0.121[0.00]***	0.018[0.00]***	0.040[0.00]***
ADF for Residuals	-3.005***	-3.041***	-3.783***	-4.059***	-1.763*	-1.793*
	soybeans-wheat		soybeans-live cattle		wheat-live cattle	
	soybeans equation	wheat equation	soybeans equation	live cattle equation	wheat equation	live cattle equation
OLS Estimators						
constant	2.125[0.00]***	0.246[0.178]	5.924[0.00]***	3.953[0.00]***	5.924[0.00]***	4.539[0.00]***
corn	-	-	-	-	-	
soybeans	-	0.870[0.00]***	-	0.120[0.00]***	-	-
wheat	0.769[0.00]***	-	-	-	-	0.040[0.178]
live cattle	-	-	0.222[0.00]***	-	0.083[0.178]	-
Durbin-Waston Statistic	0.079[0.00]***	0.093[0.00]***	0.022[0.00]***	0.041[0.00]***	0.036[0.00]***	0.040[0.00]***
ADF for Residuals	-3.181***	-3.464***	-1.840*	-1.821*	-1.793*	-1.795*

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] The ADF-test process without drift.

Table 3.4 and table 3.5 show coefficients of lagged returns and net long position change for both index traders and swap dealers. The significant effects from the lagged returns are similar in table 3.4 and table 3.5. The past returns for corn are significant in the corn-wheat model and not significant in the corn-soybeans and the corn-live cattle models on the current returns. Soybeans' past returns' results are significant for both the soybeans-corn and the soybeans-wheat model but not in the soybeans-live cattle model. The past returns of wheat show the same result with soybeans. The coefficients are significant in the wheat-corn and the wheat-soybeans model, not in the wheat-live cattle model. The live cattle past returns are generally insignificant on the current returns in all the models. The interesting thing needs to be mention is that all the significant coefficients are negative, which means the last returns have a negative contribution to the current returns. We will discuss the reason in the last chapter.

When we look at the spillovers from the past returns of live cattle to other commodities, insignificant effect is shown in all cases except the soybeans' current returns. However, the significant effect is small as well. The past returns of soybeans have significant spillovers to the corn and wheat, the past returns of corn have significant spillovers to the soybeans and wheat, and the past returns of wheat has significant spillovers to the corn and soybeans. The ECT_{t-1} in all the VECM are significant, and the signs are negative as we expected. The negative and significant ECTs indicates the long-run causal relationship. ECTs aim to correct the long-run disequilibrium of the model. The ECTs between the corn-soybeans, the corn-wheat, and the soybeans-wheat are significant in both equations, which suggests a bi-directional causality.

Based on the results from table 3.4, there is very limited evidence on the Granger-causality from the past index traders trading to the current futures returns. The current trading information of soybeans, wheat, and live cattle has a small significant effect on their own current returns. The past trading information has a strong negative impact on the current returns with value -0.012. In 5% rejection level, we only see the spillovers from the index traders trading in the current period of soybeans to the current returns of corn, the past trading of soybeans to the current returns of wheat, and the past trading of live cattle to the current returns of corn. The soybeans' past trading to the corn returns, the current soybeans trading to the wheat returns, and past wheat trading to the live cattle are significant when we release the rejection level to 10%. Surprisingly, the index traders' behavior has an insignificant effect on the current returns in all the models.

Table 3.5 indicates similar results in table 3.4. The evidence on the Granger-causality from the past swap dealers trading to the current futures returns is very limited. In 10% rejection level, only the current trading from swap dealers on soybeans and live cattle affects the current returns themselves. The spillovers only are found between the lagged wheat to current corn returns, current corn to current wheat returns, lagged corn to current live cattle returns, current live cattle to current soybeans returns, and current live cattle to current wheat returns.

3.3 BEKK-MGARCH Analysis

The BEKK-MGARCH are established in the final step upon the result of mean equations. The BEKK-MGARCH reports the estimates of H, A and B, which are not the direct coefficients of the innovation and volatility. We list the conditional covariance equations in equation 3.1 and 3.2. To specify the impact from innovation and volatility, we process the estimates to the coefficients in

Table 3.4: Conditional mean equations estimates with index traders information

	corn-soybeans		corn-wheat		corn-live cattle	
	corn equation	soybeans equation	corn equation	wheat equation	corn equation	live cattle equation
constant	-	-	-	-	0.007[0.97]	-0.019[0.87]
$r_{c,t-1}$	-0.033[0.49]	-0.179[0.00]***	-0.150[0.01]***	-0.255[0.00]***	0.026[0.54]	0.048[0.14]
$r_{w,t-1}$	-	-	-0.294[0.00]***	-0.248[0.00]***	-	-
$r_{s,t-1}$	-0.554[0.00]***	-0.305[0.00]***	-	-	-	-
$r_{l,t-1}$	-	-	-	-	-0.084[0.14]	-0.061[0.15]
ECT_{t-1}	-0.9113[0.00]***	-0.397[0.00]***	-0.654[0.00]***	-0.504[0.00]***	-	-
$\nabla NLPI_{c,t}$	0.001[0.77]	-0.001[0.61]	0.001[0.85]	-0.003[0.39]	0.002[0.39]	-0.002[0.28]
$\nabla NLPI_{c,t-1}$	-0.004[0.24]	-0.003[0.24]	-0.002[0.53]	0.004[0.20]	-0.002[0.52]	0.001[0.81]
$\nabla NLPI_{w,t}$	-	-	-0.002[0.55]	-0.005[0.07]*	-	-
$\nabla NLPI_{w,t-1}$	-	-	-0.001[0.76]	0.000[0.89]	-	-
$\nabla NLPI_{s,t}$	-0.006[0.02]**	-0.004[0.09]*	-	-	-	-
$\nabla NLPI_{s,t-1}$	0.004[0.08]*	0.003[0.13]	-	-	-	-
$\nabla NLPI_{l,t}$	-	-	-	-	0.002[0.60]	0.004[0.11]
$\nabla NLPI_{l,t-1}$	-	-	-	-	0.006[0.05]**	-0.011[0.00]***
$Q_{LB}(1)$	8.681[0.00]***	9.719[0.00]***	10.406[0.00]***	11.182[0.00]***	0.036[0.85]	0.004[0.95]
$Q_{LB}(5)$	56.204[0.00]***	44.094[0.00]***	71.604[0.00]***	62.370[0.00]***	21.412[0.00]***	5.259[0.39]
ARCH(1)	2.223[0.14]	50.348[0.00]***	26.457[0.00]***	4.119[0.04]**	17.256[0.00]***	2.307[0.13]
ARCH(5)	19.861[0.00]***	57.724[0.00]***	39.540[0.00]***	45.659[0.00]***	19.302[0.00]***	10.907[0.05]**
	soybeans-wheat		soybeans-live cattle		wheat-live cattle	
	soybeans equation	wheat equation	soybeans equation	live cattle equation	wheat equation	live cattle equation
constant	-	-	0.012[0.93]	-0.028[0.82]	0.006[0.97]	-0.021[0.86]
$r_{c,t-1}$	-	-	-	-	-	-
$r_{w,t-1}$	-0.183[0.00]***	-0.150[0.00]***	-	-	0.012[0.78]	0.042[0.17]
$r_{s,t-1}$	-0.313[0.00]***	-0.364[0.00]***	-0.000[0.99]	0.031[0.47]	-	-
$r_{l,t-1}$	-	-	-0.075[0.08]*	-0.061[0.15]	-0.008[0.89]	-0.055[0.20]
ECT_{t-1}	-0.369[0.00]***	-0.763[0.00]***	-	-	-	-
$\nabla NLPI_{c,t}$	-	-	-	-	-	-
$\nabla NLPI_{c,t-1}$	-	-	-	-	-	-
$\nabla NLPI_{w,t}$	0.000[0.92]	-0.004[0.14]	-	-	-0.005[0.02]**	-0.001[0.56]
$\nabla NLPI_{w,t-1}$	-0.001[0.78]	0.000[0.96]	-	-	-0.000[0.86]	0.003[0.09]*
$\nabla NLPI_{s,t}$	-0.005[0.02]**	-0.004[0.09]*	-0.003[0.07]*	-0.001[0.61]	-	-
$\nabla NLPI_{s,t-1}$	-0.003[0.14]	0.007[0.01]***	0.002[0.19]	-0.001[0.43]	-	-
$\nabla NLPI_{l,t}$	-	-	0.001[0.75]	0.004[0.09]*	-0.003[0.42]	-0.004[0.08]*
$\nabla NLPI_{l,t-1}$	-	-	-0.002[0.39]	-0.012[0.00]***	0.003[0.44]	-0.012[0.00]***
$Q_{LB}(1)$	10.719[0.00]***	4.997[0.03]**	0.029[0.87]	0.007[0.93]	0.014[0.91]	0.009[0.93]
$Q_{LB}(5)$	44.565[0.00]***	34.506[0.00]	1.438[0.92]	4.944[0.42]	12.553[0.02]**	4.995[0.42]
ARCH(1)	37.935[0.00]***	1.252[0.26]	9.221[0.00]***	-2.500[0.11]	1.039[0.31]	2.000[0.16]
ARCH(5)	45.992[0.00]***	36.695[0.00]***	14.400[0.01]**	10.560[0.06]*	36.495[0.00]***	9.255[0.10]*

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] Subscribes c,w,s and l denote corn, wheat, soybeans and live cattle.

equation 3.1 and 3.2. The impact from own past shocks to the returns in commodity i represented by $\varepsilon^2_{i,t-1}$, a mixed effect from the past shocks to the returns in commodity i represented by $\varepsilon_{i,t-1} \cdot \varepsilon_{j,t-1}$, and a spillovers from the other commodity's past shock to the current returns of commodity i can be explained by the coefficient of $\varepsilon^2_{j,t-1}$. The volatility impacts from the past volatility of commodity i to the current volatility of commodity i is represented by the coefficients of $h_{ii,t-1}$, the mixed impact is explained by the coefficients of $h_{ij,t-1}$, and the spillovers accounted by the

Table 3.5: Conditional mean equations estimates with swap dealers information

	corn-soybeans		corn-wheat		corn-live cattle	
	corn equation	soybeans equation	corn equation	wheat equation	corn equation	live cattle equation
constant	-	-	-	-	0.027[0.87]	-0.030[0.80]
$r_{c,t-1}$	-0.056[0.24]	-0.192[0.00]***	-0.146[0.01]***	-0.253[0.00]***	0.027[0.53]	0.056[0.09]*
$r_{w,t-1}$	-	-	-0.297[0.00]***	-0.251[0.00]***	-	-
$r_{s,t-1}$	-0.555[0.00]***	-0.289[0.00]***	-	-	-	-
$r_{l,t-1}$	-	-	-	-	-0.095[0.09]*	-0.074[0.08]*
ECT_{t-1}	-0.884[0.00]***	-0.427[0.00]***	-0.660[0.00]***	-0.503[0.00]***	-	-
$\nabla NLPS_{c,t}$	0.043[0.29]	0.043[0.20]	0.058[0.17]	0.074[0.10]*	0.045[0.22]	-0.028[0.31]
$\nabla NLPS_{c,t-1}$	0.004[0.93]	0.012[0.73]	-0.032[0.45]	-0.036[0.43]	-0.008[0.83]	0.068[0.02]**
$\nabla NLPS_{w,t}$	-	-	-0.037[0.36]	-0.023[0.60]	-	-
$\nabla NLPS_{w,t-1}$	-	-	0.075[0.06]*	0.054[0.21]	-	-
$\nabla NLPS_{s,t}$	-0.008[0.77]	0.029[0.22]	-	-	-	-
$\nabla NLPS_{s,t-1}$	0.019[0.49]	-0.005[0.83]	-	-	-	-
$\nabla NLPS_{l,t}$	-	-	-	-	0.007[0.91]	-0.078[0.12]
$\nabla NLPS_{l,t-1}$	-	-	-	-	0.015[0.82]	-0.027[0.60]
$Q_{LB}(1)$	9.909[0.00]***	8.040[0.00]***	9.874[0.00]***	11.943[0.00]***	0.016[0.90]	0.001[0.98]
$Q_{LB}(5)$	54.747[0.000]***	42.399[0.00]***	64.563[0.00]***	60.567[0.00]***	21.166[0.00]***	7.286[0.20]
ARCH(1)	2.446[0.12]	54.314[0.00]***	23.675[0.00]***	3.227[0.07]*	14.003[0.00]***	4.587[0.03]**
ARCH(5)	19.360[0.00]***	62.737[0.00]***	35.433[0.00]***	36.261[0.00]***	16.079[0.01]***	29.630[0.00]***
	soybeans-wheat		soybeans-live cattle		wheat-live cattle	
	soybeans equation	wheat equation	soybeans equation	live cattle equation	wheat equation	live cattle equation
constant	-	-	0.013[0.92]	-0.034[0.78]	-0.008[0.96]	-0.029[-0.82]
$r_{c,t-1}$	-	-	-	-	-	-
$r_{w,t-1}$	-0.192[0.00]***	-0.170[0.00]***	-	-	0.015[0.73]	0.036[0.25]
$r_{s,t-1}$	-0.296[0.00]***	-0.361[0.00]***	-0.005[0.91]	0.019[0.66]	-	-
$r_{l,t-1}$	-	-	-0.072[0.09]*	-0.076[0.07]*	-0.004[0.95]	-0.072[0.09]*
ECT_{t-1}	-0.401[0.00]***	-0.729[0.00]***	-	-	-	-
$\nabla NLPS_{c,t}$	-	-	-	-	-	-
$\nabla NLPS_{c,t-1}$	-	-	-	-	-	-
$\nabla NLPS_{w,t}$	-0.004[0.89]	-0.001[0.98]	-	-	-0.020[0.59]	0.004[0.87]
$\nabla NLPS_{w,t-1}$	0.018[0.57]	0.044[0.27]	-	-	0.021[0.57]	0.033[0.22]
$\nabla NLPS_{s,t}$	0.041[0.08]*	0.031[0.30]	0.037[0.06]*	0.022[0.27]	-	-
$\nabla NLPS_{s,t-1}$	0.006[0.80]	0.002[0.96]	-0.002[0.93]	-0.015[0.45]	-	-
$\nabla NLPS_{l,t}$	-	-	0.087[0.09]*	-0.098[0.05]**	0.181[0.01]***	-0.093[0.07]*
$\nabla NLPS_{l,t-1}$	-	-	-0.052[0.31]	-0.005[0.92]	-0.063[0.37]	-0.021[0.68]
$Q_{LB}(1)$	8.250[0.00]***	5.574[0.02]**	0.141[0.71]	0.048[0.83]	0.026[0.87]	0.049[0.82]
$Q_{LB}(5)$	40.921[0.00]***	37.878[0.00]***	2.828[0.73]	6.115[0.30]	9.102[0.10]*	6.500[0.26]
ARCH(1)	37.649[0.00]***	1.168[0.28]	10.349[0.00]***	4.389[0.04]**	0.776[0.38]	5.049[0.02]**
ARCH(5)	45.367[0.00]***	34.052[0.00]***	15.889[0.01]***	30.747[0.00]***	30.543[0.00]***	33.825[0.00]***

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] Subscribes c,w,s and l denote corn, wheat, soybeans and live cattle.

coefficients of $h_{jj,t-1}$.

$$\begin{aligned} h_{11,t} &= c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}^2\varepsilon_{2,t-1}^2 \\ &\quad + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} \end{aligned} \tag{3.1}$$

$$
\begin{aligned}
h_{22,t} = c_{22}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + 2a_{22}a_{12}\varepsilon_{2,t-1}\varepsilon_{1,t-1} + a_{12}^2\varepsilon_{1,t-1}^2 \\
+ b_{22}^2 h_{22,t-1} + 2b_{22}b_{12}h_{12,t-1} + b_{12}^2 h_{11,t-1}
\end{aligned}
\tag{3.2}
$$

Table 3.6 and table 3.7 list the results of conditional covariance equations estimates with index traders trading and swap dealers trading information. Except for the past innovation of corn in the corn-soybeans model, all other past innovations have a significant and positive effect on the current volatility in 5% rejection level. The spillovers from the past shocks to other commodities' volatility are significant in 5% significant level for bi-direction between corn and soybeans in the corn-soybeans model, bi-direction between corn and wheat in the corn-wheat model, live cattle to corn in the corn-live cattle model, and wheat to live cattle in the wheat-live cattle model. The current volatility depends on the past volatility in the same commodity is significant for corn and soybeans in the corn-soybeans model, corn and wheat in the corn-wheat model, corn and live cattle in the corn-live cattle model, soybeans and wheat in the soybeans-wheat model, soybeans and live cattle in the soybeans-live cattle model, wheat and live cattle in the wheat-soybeans cattle model. The spillovers are significant for soybeans to corn and corn to soybeans in the corn-soybeans model, wheat to corn in corn-wheat model, and live cattle to corn in corn-live cattle model. The cross-volatility indirect spillovers are found in the corn-soybeans model, the corn-wheat model, the corn-live cattle model, and the wheat-live cattle model. The coefficients are negative and significant for corn in the corn-soybeans model, corn in the corn-wheat model, and live cattle in wheat live cattle model. Positive and significant coefficients are shown on soybeans in the corn-soybeans model, wheat in the corn-wheat model, and corn in the corn-live cattle model. The current index traders' trading affect their own current volatility in corn at the corn-soybeans model and the corn-live cattle model. The same effect also have been found in live cattle in the corn-live cattle model. The squared trading information indicates significant effects between commodities like the corn-wheat, the corn-live cattle, and the live cattle-soybeans. Table 3.7 tells us that the swap dealers' contemporaneous trading information affects the volatility of corn itself in general. The live cattle's current trading information from swap dealers have a significant impact on the

Table 3.6: BEKK-MGARCH estimates with index traders information

	corn-soybeans		corn-wheat		corn-live cattle	
	corn equation	soybeans equation	corn equation	wheat equation	corn equation	live cattle equation
constant	1.362[0.00]***	0.0523[0.26]	0.651[0.11]	3.764[0.00]***	0.411[0.03]**	4.871[0.00]***
$\varepsilon^2_{c,t-1}$	0.020[0.06]*	0.048[0.00]***	0.078[0.00]***	0.150[0.00]***	0.188[0.00]***	0.006[0.09]*
$\varepsilon^2_{s,t-1}$	0.049[0.02]**	0.251[0.00]***	-	-	-	-
$\varepsilon^2_{w,t-1}$	-	-	0.053[0.00]***	0.063[0.00]***	-	-
$\varepsilon^2_{l,t-1}$	-	-	-	-	0.034[0.01]***	0.092[0.00]***
$\varepsilon_{c,t-1}\varepsilon_{s,t-1}$	0.062[0.04]**	-0.218[0.00]***	-	-	-	-
$\varepsilon_{c,t-1}\varepsilon_{w,t-1}$	-	-	0.128[0.00]***	-0.194[0.00]***	-	-
$\varepsilon_{c,t-1}\varepsilon_{l,t-1}$	-	-	-	-	-0.160[0.00]***	0.047[0.05]**
$h_{cc,t-1}$	0.929[0.00]***	0.194[0.00]***	1.065[0.000]***	0.034[0.05]*	0.700[0.00]***	0.001[0.55]
$h_{ss,t-1}$	0.666[0.00]***	0.210[0.00]***	-	-	-	-
$h_{ww,t-1}$	-	-	0.200[0.00]***	0.484[0.00]***	-	-
$h_{ll,t-1}$	-	-	-	-	0.069[0.01]***	0.265[0.00]***
$h_{cs,t-1}$	-1.574[0.000]***	0.404[0.00]***	-	-	-	-
$h_{cw,t-1}$	-	-	-0.923[0.00]***	0.257[0.00]***	-	-
$h_{cl,t-1}$	-	-	-	-	0.440[0.00]***	-0.025[0.27]
$\nabla NLPI_{c,t}$	-0.005[0.03]**	0.003[0.17]	0.003[0.41]	-0.005[0.03]**	0.013[0.00]***	0.001[0.77]
$\nabla NLPI^2_{c,t}$	0.001[0.52]	0.005[0.08]*	-0.008[0.00]***	-0.011[0.00]***	-0.002[0.49]	-0.011[0.00]***
$\nabla NLPI_{s,t}$	0.003[0.14]	-0.001[0.48]	-	-	-	-
$\nabla NLPI^2_{s,t}$	0.000[0.92]	-0.001[0.56]	-	-	-	-
$\nabla NLPI_{w,t}$	-	-	0.001[0.59]	0.001[0.57]]	-	-
$\nabla NLPI^2_{w,t}$	-	-	0.000[0.90]	0.001[0.67]	-	-
$\nabla NLPI_{l,t}$	-	-	-	-	-0.000[0.88]	0.007[0.01]***
$\nabla NLPI^2_{l,t}$	-	-	-	-	0.009[0.06]**	0.001[0.66]*
$\nabla NLPI_{c,t}\nabla NLPI_{s,t}$	-0.002[0.47]	-0.003[0.24]	-	-	-	-
$\nabla NLPI_{c,t}\nabla NLPI_{w,t}$	-	-	0.002[0.66]	0.001[0.62]	-	-
$\nabla NLPI_{c,t}\nabla NLPI_{l,t}$	-	-	-	-	-0.002[0.53]	0.004[0.06]*
$Q_{LB}(1)$	1.129[0.29]	0.368[0.54]	0.607[0.44]	0.367[0.54]	0.787[0.38]	0.077[0.78]
$Q_{LB}(4)$	5.857[0.21]	2.801[0.59]	6.989[0.14]	9.603[0.05]**	3.644[0.46]	6.806[0.15]
	soybeans-wheat		soybeans-live cattle		wheat-live cattle	
	soybeans equation	wheat equation	soybeans equation	live cattle equation	wheat equation	live cattle equation
constant	1.428[0.00]***	1.055[0.00]***	1.445[0.00]***	1.367[0.00]***	0.987[0.00]***	1.597[0.00]***
$\varepsilon^2_{s,t-1}$	0.151[0.00]***	0.004[0.60]	0.207[0.00]***	0.000[0.99]	-	-
$\varepsilon^2_{w,t-1}$	0.005[0.15]	0.079[0.00]***	-	-	0.084[0.00]***	0.012[0.05]**
$\varepsilon^2_{l,t-1}$	-	-	0.000[0.91]	0.116[0.00]***	0.002[0.64]	0.123[0.00]***
$\varepsilon_{s,t-1}\varepsilon_{w,t-1}$	0.056[0.08]*	-0.037[0.30]	-	-	-	-
$\varepsilon_{s,t-1}\varepsilon_{l,t-1}$	-	-	-0.006[0.46]	-0.000[0.50]	-	-
$\varepsilon_{w,t-1}\varepsilon_{l,t-1}$	-	-	-	-	-0.023[0.32]	0.078[0.02]**
$h_{ss,t-1}$	0.585[0.00]***	0.001[0.80]	0.621[0.00]***	0.001[0.47]	-	-
$h_{ww,t-1}$	0.003[0.60]	0.839[0.00]***	-	-	0.851[0.00]***	0.005[0.06]
$h_{ll,t-1}$	-	-	0.001[0.55]	0.711[0.00]***	0.001[0.73]	0.635[0.00]***
$h_{sw,t-1}$	0.077[0.30]	0.058[0.40]	-	-	-	-
$h_{sl,t-1}$	-	-	-0.044[0.27]	0.059[0.24]	-	-
$h_{wl,t-1}$	-	-	-	-	0.068[0.36]	-0.113[0.03]**
$\nabla NLPI_{s,t}$	-0.002[0.38]	0.002[0.24]	-0.001[0.50]	0.002[0.12]	-	-
$\nabla NLPI^2_{s,t}$	0.002[0.23]	-0.001[0.55]	0.002[0.11]	-0.001[0.49]	-	-
$\nabla NLPI_{w,t}$	-0.000[0.79]	-0.000[0.98]	-	-	-0.000[0.80]	-0.002[0.23]
$\nabla NLPI^2_{w,t}$	-0.000[0.94]	-0.001[0.74]	-	-	-0.005[0.00]***	-0.000[0.88]
$\nabla NLPI_{l,t}$	-	-	-0.005[0.05]**	0.001[0.82]	-0.002[0.51]	0.001[0.67]
$\nabla NLPI^2_{l,t}$	-	-	-0.003[0.36]	-0.004[0.21]	0.004[0.54]	-0.001[0.74]
$\nabla NLPI_{s,t}\nabla NLPI_{w,t}$	-0.002[0.40]	0.000[0.90]	-	-	-	-
$\nabla NLPI_{s,t}\nabla NLPI_{l,t}$	-	-	-0.001[0.55]	0.001[0.57]	-	-
$\nabla NLPI_{w,t}\nabla NLPI_{l,t}$	-	-	-	-	0.000[0.84]	-0.000[0.94]
$Q_{LB}(1)$	0.000[0.99]	3.225[0.08]*	0.015[0.90]	0.033[0.86]	0.071[0.79]	0.291[0.59]
$Q_{LB}(4)$	1.694[0.79]	10.458[0.04]**	1.803[0.77]	8.823[0.07]*	12.257[0.02]**	8.795[0.07]*

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] Subscribes c,w,s and l denote corn, wheat, soybeans and live cattle.

Table 3.7: BEKK-MGARCH estimates with swap dealers information

	corn-soybeans		corn-wheat		corn-live cattle	
	corn equation	soybeans equation	corn equation	wheat equation	corn equation	live cattle equation
$\nabla NLPS_{c,t}$	-0.020[0.47]	-0.050[0.08]*	-0.100[0.01]***	0.051[0.08]*	-0.082[0.00]***	-0.007[0.83]
$\nabla NLPS^2_{c,t}$	0.012[0.80]	0.019[0.58]	0.032[0.60]	0.083[0.11]	0.051[0.06]*	-0.081[0.03]**
$\nabla NLPS_{s,t}$	-0.052[0.05]**	0.059[0.00]***	-	-	-	-
$\nabla NLPS^2_{s,t}$	0.045[0.07]*	-0.028[0.24]	-	-	-	-
$\nabla NLPS_{w,t}$	-	-	0.022[0.49]	0.029[0.34]	-	-
$\nabla NLPS^2_{w,t}$	-	-	0.054[0.18]	-0.032[0.42]	-	-
$\nabla NLPS_{l,t}$	-	-	-	-	-0.38[0.00]***	-0.118[0.02]**
$\nabla NLPS^2_{l,t}$	-	-	-	-	-0.200[0.00]***	-0.393[0.00]***
$\nabla NLPS_{c,t}\nabla NLPS_{s,t}$	-0.047[0.12]	0.040[0.17]	-	-	-	-
$\nabla NLPS_{c,t}\nabla NLPS_{w,t}$	-	-	0.008[0.91]	0.046[0.12]	-	-
$\nabla NLPS_{c,t}\nabla NLPS_{l,t}$	-	-	-	-	-0.025[0.33]	0.291[0.00]***
$Q_{LB}(1)$	1.711[0.19]	0.774[0.38]	0.048[0.83]	0.333[0.56]	0.641[0.42]	0.374[0.54]
$Q_{LB}(4)$	5.570[0.23]	2.050[0.73]	3.981[0.41]	8.195[0.08]*	3.941[0.41]	9.353[0.06]*
	soybeans-wheat		soybeans-live cattle		wheat-live cattle	
	soybeans equation	wheat equation	soybeans equation	live cattle equation	wheat equation	live cattle equation
$\nabla NLPS_{s,t}$	0.041[0.11]	-0.011[0.62]	0.026[0.31]	-0.224[0.00]***	-	-
$\nabla NLPS^2_{s,t}$	-0.009[0.67]	0.026[0.50]	0.003[0.89]	-0.039[0.49]	-	-
$\nabla NLPS_{w,t}$	-0.001[0.96]	0.011[0.79]	-	-	-0.002[0.95]	0.078[0.00]***
$\nabla NLPS^2_{w,t}$	0.021[0.53]	0.008[0.76]	-	-	0.062[0.03]**	0.002[0.95]
$\nabla NLPS_{l,t}$	-	-	-0.96[0.09]*	-0.224[0.00]***	0.003[0.96]	-0.245[0.00]***
$\nabla NLPS^2_{l,t}$	-	-	-0.157[0.01]**	-0.039[0.49]	-0.229[0.00]***	0.012[0.84]
$\nabla NLPS_{s,t}\nabla NLPS_{w,t}$	-0.012[0.73]	0.006[0.85]	-	-	-	-
$\nabla NLPS_{s,t}\nabla NLPS_{l,t}$	-	-	0.011[0.54]	-0.092[0.08]*	-	-
$\nabla NLPS_{w,t}\nabla NLPS_{l,t}$	-	-	-	-	0.044[0.23]	-0.008[0.88]
$Q_{LB}(1)$	0.269[0.60]	3.389[0.07]*	0.048[0.83]	0.085[0.77]	0.034[0.85]	0.008[0.93]
$Q_{LB}(4)$	0.882[0.93]	12.804[0.02]**	0.616[0.96]	7.246[0.12]	9.148[0.06]*	8.926[0.06]*

[a] P-values in square brackets.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] Subscribes c,w,s and l denote corn, wheat, soybeans and live cattle.

volatility of live cattle futures returns in all the models. Further, the influence from the squared trading position change also be detected in corn, wheat, and soybeans. The soybeans trading have a significant impact on live cattle in soybean-live cattle model and corn in the corn-soybeans model.

3.3.1 COVID-19 and Section 301 Tariff Action impacts

During the year 2019 and 2020, there are two main global risks that affect the global economy. The United States Trade Representative (USTR) announces the initiation of section 301 investigation of China on 08/18/2017, and we assume the uncertainty global economy affects the returns and volatility of agricultural commodity futures, particularly in soybeans and corn. As a non-storable product, we are not expecting a significant change in the live cattle market. The impact from the trader negotiation might be explained partly in the trading volume in index traders or swap dealers, the dummy variables will not be added into the former equations. The influence of the COVID-19 pandemic also be considered in this section. We set up a dummy on 03/17/2020, which is the nearest date that accompanies with the white house proclamation on declaring a national emergency concerning the COVID-19 outbreak. Three significant dates have been considered as shocks of the market in this paper. The WHO characterizes the COVID-19 as a pandemic at 3/11/2020 which is really close to the dummy set before, it could influence the market at the same time. However, the COVID-19 is begin at the later January 2020, the impact may be spread to the period between January and March.

Table 3.8: BEKK-MGARCH estimates of mean equations with dummy variables

	corn-soybeans		corn-wheat		soybeans-wheat		soybeans-live cattle	
	$r_{c,t}$	$r_{s,t}$	$r_{c,t}$	$r_{w,t}$	$r_{s,t}$	$r_{w,t}$	$r_{s,t}$	$r_{l,t}$
$UC17$	-0.509(2.42)	-0.969(1.90)	-1.555(2.04)	0.355(5.45)	-0.780(1.77)	1.001(4.72)	-0.852(1.93)	-2.183(4.11)
$UC19$	0.844(4.38)	-5.925(2.97)**	1.265(7.89)	-0.421(5.03)	-5.403(2.63)**	-0.520(2.73)	-5.499(2.45)**	1.565(2.62)
$UC20$	-0.391(2.38)	3.101(2.11)	1.114(2.11)	3.756(2.54)	3.181(1.93)*	2.585(2.68)	3.320(2.03)*	1.686(3.75)
$COVID$	0.922(4.95)	-1.913(3.73)	-0.148(6.86)	-5.429(4.54)	-1.793(2.72)	-5.106(3.20)	-1.784(2.49)	-1.803(5.44)

[a] Standard error in parentheses.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] Subscribes c,w,s and l denote corn, wheat, soybeans and live cattle.
[d] UC17, US19, US20 represents the dummy in 08/29/2017, 05/21/2019, 01/21/2020, and COVID represents the dummy in 03/17/2020.

Table 3.9: BEKK-MGARCH estimates with dummy variables

	corn-soybeans		corn-wheat		soybeans-wheat		soybeans-live cattle	
	$h_{cc,t}$	$h_{ss,t}$	$h_{cc,t}$	$h_{ww,t}$	$h_{ss,t}$	$h_{ww,t}$	$h_{ss,t}$	$h_{ll,t}$
$UC17$	1.535(1.69)	0.449(2.21)	-1.620(1.79)	-5.526(2.09)***	-1.478(1.81)	3.723(2.09)*	-1.919(1.83)	-3.058(1.80)*
$UC19$	3.319(1.95)*	-1.658(2.10)	4.532(3.34)	2.415(1.87)	-0.910(4.68)	-0.634(4.72)	-1.195(2.96)	-0.176(3.81)
$UC20$	-0.568(2.18)	0.015(1.82)	-1.329(1.51)	-0.316(1.63)	-1.258(1.63)	-0.277(2.14)	-1.195(1.63)	-0.176(1.95)
$COVID$	4.187(1.76)**	2.279(1.56)	5.347(2.90)*	-2.941(1.621)*	0.441(1.63)	-1.476(1.566)	-1.195(2.99)	-0.129(4.13)

[a] Standard error in parentheses.
[b] Rejections at the 1% level are denoted by ***, 5% level by ** and 10% by *.
[c] Subscribes c,w,s and l denote corn, wheat, soybeans and live cattle.
[d] UC17, US19, US20 represents the dummy in 08/29/2017, 05/21/2019, 01/21/2020, and COVID represents the dummy in 03/17/2020.

The first one, 08/24/2017, is the date that announcement of the initiation of section 301 investigation reported by the Office of the United States Trade Representative, and the second one, 01/15/2020, is the date that economic and trade agreement between the United States and China have been signed. We set the dummy 1 at the nearest following date with our data, and 0 otherwise. 05/17/2019 is added into our model due to the date that USTR publishes the products imported from China will be charged for an additional tariff. Adding the pandemic dummy 1 on 03/17/2020, and 0 otherwise. In general, The COVID dummy describes the date of the white house announcement of a national emergency. UC17 is the dummy describe the initiation of section 301 investigation of China, US19 is the dummy describes the public of production list needs to be imposed with additional tariff. UC20 is the dummy describes the agreement of economic and trade between the United States and China. We apply the VAR-BEKK-MGARCH or VECM-BEKK-MGARCH to find the result. The results are reported in table 3.8 and 3.9.

In table 3.8, the US-China trade negotiation has very limited influence on futures returns in agricultural commodity, and we only see the significant coefficient for the returns of soybeans from UC19 and UC20 in 10% rejection level. The results indicate that the US-China negotiation is not likely to be influenced much the futures returns in agricultural commodities besides the soybeans. When we look at the variance equation, the conditional variance of wheat is affected significantly by the US17, and the conditional variance of corn is influenced by the COVID-19 pandemic.

4. SUMMARY AND CONCLUSIONS

Due to the COVID-19 Pandemic and the Locust Crisis, global food production is negatively affected. Furthermore, an uncertain financial environment fluctuates the returns and volatility of financial markets, like the stock market and futures/options market. We use bivariate VAR/VECM models as mean equations of MGARCH models to find the spillovers across the futures returns and volatility for corn, soybeans, wheat, and live cattle. We add the logarithm net long position change of index traders and swap dealers reported by CFTC's Commitments of Traders Reports, which are published every Tuesday, as exogenous variables in the models. We also set up dummy variables to evaluate the influence from the US-China trade negotiation and the COVID-19 pandemic. The paper shows evidence that the own past returns have significant effects on the current returns for soybeans futures and wheat futures. The impact from the corn futures and live cattle futures are not be found in our research. In addition, the spillovers between the corn and soybeans, corn and wheat, soybeans and wheat are bidirectional. The spillovers from the storable commodities and the non-storable commodity, live cattle, are insignificant. The own past volatility significantly affects the current volatility for all the commodities in the BEKK model. The past shock positively affects the current volatility for the commodities as well, which are consistent with Lopez and Dawson(2017). The spillovers from the past innovations to the current volatility are observed in the corn-soybeans, the corn-wheat bidirectional. There is a single direction effect from live cattle to corn and wheat to live cattle. The spillovers from the past volatility to the current volatility are found in the corn-soybeans, the corn-wheat bidirectional, and a single direction from live cattle to corn. The spillovers from the corn-soybeans are consistent with the result of Zhao and Goodwin(2011). In summary, the spillovers between the corn-soybeans and the corn-wheat are strong both in returns and volatility. The coefficients are negative in the returns spillovers and positive in the volatility spillovers. We consider commodity substitution as a reason for spillovers in returns between corn and soybeans. The relationship between corn and wheat is complex. One view is that the wheat market tends to follow the corn market, which is not consistent with negative spillovers coefficient in returns as we figure out. Another point is that the two commodities are somewhat substitutable in the feed grain markets. The data shows that the feed grain market consumes an average 19% of wheat production and 68% if corn production. The spillovers between soybeans and wheat in returns are significant, which can be explained by the substitution effect in the feed and ethanol production use of these two commodities.

The key topic of the paper is discussing the impact from the index traders and swap dealers trading on the futures returns and volatility. For the part of index traders, the results indicate a weak negative effect from the contemporaneous position changes on the current returns for both wheat and soybeans, and a strong negative effect from the first-lag period position changes on the current returns for live cattle. In contrast, the impact is not observed in corn. We interpret the sign of coefficient that a large position change may be caused by the market shock, which negatively affect the returns in most cases. The EMH is not satisfied with all the commodities. The own swap dealers net long position change have insignificant impacts on all the commodities except the live cattle, which is not accompanied with our expectation. The spillovers in returns exist in the soybeans-corn contemporaneously, and the live cattle-corn and the soybeans-wheat with the lagged position change when we apply the index traders' trading inside. The swap dealers trading indicates the spillovers in returns only between the corn-live cattle model with lagged position change and the live cattle-wheat contemporaneously. The index traders' position change for corn has significant positive effect on the current volatility. A similar effect also has been found in live cattle in the corn-live cattle model. We attributed the reason that a high volume position change lead to a high volatility. The spillovers that the index traders position change from corn to the wheat volatility are observed, and the live cattle position change to soybeans volatility is found as well. The spillovers accompany with negative coefficient, which is expected. The swap dealers data gives a slightly different result. The corn trading significantly affects the current volatility in the corn-wheat model and the corn-live cattle model. Soybeans trading position change from swap dealers have impacts on its own volatility only in the corn-soybeans model. The swap dealers trading in live cattle are significantly affect the current volatility in all models. The soybeans' net long position change from swap dealers has spillovers on the corn's and live cattle's current volatility. A similar impact is observed from live cattle to corn and wheat to live cattle. Overall, the corn and live cattle trading information is more likely to affect the volatility rather than soybeans and wheat. The index trading and swap dealers' trading are more likely to reduce their own volatility, which is consistent with Sanders and Irwin (2011b), Hamilton and Wu (2015). The spillovers are found in different commodities based on the index traders' information and swap dealers information.

As an extension of this paper, we explore the impact from the US-China trade negotiation and COVID-19 pandemic in the last part as an additional attempt. The COVID-19 pandemic seems to have no significant impact on the returns of the futures and only have impact on the corn's volatility. The reason of that can be explained by the inelastic demand of the agricultural commodities. We originally expect the impact on the returns and volatility from the environment change of the transportation, storage level and consumption. A further study is worth to do to explore the Covid-19 impact with more variables added to the model to discuss more details. The US19 only has a significant effect on the soybeans' returns, which may caused by the reason that China is the main country that the United States soybeans export to. The other impact is generally insignificant except the UC17 on the volatility of wheat. The result is very simple and preliminary. It could be a starting point for future research.

The suggestion for hedgers is a little bit complicated. We make the suggestion into two concerns; the first one is the price expectation for the coming period, and the other is the volatility modification of the market. The strategy of the storable commodity hedgers and non-storable commodity hedgers should be different. We give an example of the live cattle hedgers who also need to concern the price change for the feed grains like corn. We rarely find a significant impact from the past returns on the current returns. However, both the index traders and swap dealers trading volume affect the returns of live cattle futures. We can find the negative effect from the t-1 period of the index traders' net long position change to the live cattle's returns. We also observe the impact of the swap dealers' net long position change contemporaneously. We prefer to suggest to focus on the past period impact, which is much easier to observe and have time to react without a lot of risks. With a large index traders' net long position hold for live cattle, live cattle's returns expect to decrease next period. The price of the live cattle futures will remain relatively at a low level, and the hedgers can modify their position during the period. The spillovers on the returns from the storable commodity are not significant as well. When it comes to volatility, it tells a different story. Hedgers need to pay attention to the commodity's own fluctuation, and a fluctuation could be continuous as we conclude from our result. Both a large long position held by the index traders or swap dealers can reduce the volatility, which can potentially stabilize the market. Besides, the hedgers who have live cattle in reality also need to concern the corn's futures contract, which is the primary grain they use. The spillover effect between the corn and live cattle are weak on the returns. In contrast, the volatility is closely related to each other. When the hedgers want to have a nice strategy, they need to look at the corn itself and other related storable commodities.

In general, the two main participants in agricultural futures do have their influence in the market. The effect from index traders and swap dealers are not the same across the commodities. The producers (farmers) expects a higher price of futures. The producers, merchant, and processors will benefit for lower volatility. Our findings indicate that a higher net long position hold by index traders or swap dealers increases the returns. The past shocks and volatility are positively related to the market risk within or across the commodities. Even though the impact from own index traders and swap dealers net long position change on the current volatility is limit, they decrease the volatility with the negative coefficients in most cases. This result is consistent with Sanders and Irwin (2010). The spillovers also show the same results. To ensure the futures market have sufficient liquidity, CFTC may not limit the index traders and swap dealers investment. Furthermore, the swap dealers net long position rises the returns of futures and both of their net long position decrease the volatility of the market. Finally, The investors need to know that the futures price is always up and down frequently to reach an equilibrium price as the market expects.

The paper is preliminary research on the agricultural futures market. International factors, like the foreign futures market and the exchange rate, need to be considered with globalization to improve the accuracy of the model. The speculators' behavior also be an important component when we discuss the returns and volatility in the futures market. The crude oil impact and the storage volume of the storable commodities also be the concerns on the returns of futures we discussed. We will improve the paper in the further research and give a more comprehensive result.

REFERENCES

Beckmann, J., and R. Czudaj. 2014. "Volatility transmission in agricultural futures markets." *Economic Modelling* 36:541–546.

Caporin, M., and M. McAleer. 2012. "Do we really need both BEKK and DCC? A tale of two multivariate GARCH models." *Journal of Economic Surveys* 26:736–751.

Chang, K.L., and C. Lee. 2020. "The asymmetric spillover effect of the Markov switching mechanism from the futures market to the spot market." *International Review of Economics & Finance* 69:374–388.

Chauhan, A.K., S. Singh, and A. Arora. 2013. "Market efficiency and volatility spillovers in futures and spot commodity market: The agricultural sector perspective." *Samvad* 6:61–84.

Dewbre, J., C. Giner, W. Thompson, and M. Von Lampe. 2008. "High food commodity prices: will they stay? Who will pay?" *Agricultural Economics* 39:393–403.

Engle, R.F. 1982. "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation." *Econometrica: Journal of the Econometric Society*, pp. 987–1007.

Engle, R.F., and C.W. Granger. 1987. "Co-integration and error correction: representation, estimation, and testing." *Econometrica: journal of the Econometric Society*, pp. 251–276.

Engle, R.F., and K.F. Kroner. 1995. "Multivariate simultaneous generalized ARCH." *Econometric theory*, pp. 122–150.

Engle, R.F., and K. Sheppard. 2001. "Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH." Working paper, National Bureau of Economic Research.

Garbade, K.D., and W.L. Silber. 1983. "Price movements and price discovery in futures and cash markets." *The Review of Economics and Statistics*, pp. 289–297.

Geoffrey Booth, G., P. Brockman, and Y. Tse. 1998. "The relationship between US and Canadian wheat futures." *Applied Financial Economics* 8:73–80.

Geoffrey Booth, G., and C. Ciner. 2001. "Linkages among agricultural commodity futures prices:

evidence from Tokyo." *Applied Economics Letters* 8:311–313.

Gilbert, C.L. 2010. "How to understand high food prices." *Journal of agricultural economics* 61:398–425.

Gilbert, C.L., and S. Pfuderer. 2014. "The role of index trading in price formation in the grains and oilseeds markets." *Journal of Agricultural Economics* 65:303–322.

Hamilton, J.D., and J.C. Wu. 2015. "Effects of index-fund investing on commodity futures prices." *International economic review* 56:187–205.

—. 2014. "Risk premia in crude oil futures prices." *Journal of International Money and Finance* 42:9–37.

Hernandez, M.A., R. Ibarra, and D.R. Trupkin. 2014. "How far do shocks move across borders? Examining volatility transmission in major agricultural futures markets." *European Review of Agricultural Economics* 41:301–325.

Herwartz, H., and A. Saucedo. 2020. "Food–oil volatility spillovers and the impact of distinct biofuel policies on price uncertainties on feedstock markets." *Agricultural Economics* 51:387–402.

Hochman, G., D. Rajagopal, G.R. Timilsina, and D. Zilberman. 2014. "Impacts of biofuels on food prices." In *The impacts of biofuels on the economy, environment, and poverty*. Springer, pp. 47–64.

Irwin, S.H., and D.R. Sanders. 2010. "The Impact of Index and Swap Funds on Commodity Futures Markets: Preliminary Results." OECD Food, Agricultural and Fisheries Working paper.

—. 2011. "Index funds, financialization, and commodity futures markets." *Applied Economic Perspectives and Policy* 33:1–31.

Ljung, G.M., and G.E. Box. 1978. "On a measure of lack of fit in time series models." *Biometrika* 65:297–303.

Malesios, C., N. Jones, and A. Jones. 2020. "A change-point analysis of food price shocks." *Climate Risk Management* 27:100208.

Malliaris, A.G., J.L. Urrutia, et al. 1996. "Linkages between agricultural commodity futures contracts." *Journal of Futures Markets* 16:595–609.

—. 1998. "Volume and price relationships: hypotheses and testing for agricultural futures." *Journal of Futures Markets* 18:53–72.

McLeod, A.I., and W.K. Li. 1983. "Diagnostic checking ARMA time series models using squared-residual autocorrelations." *Journal of time series analysis* 4:269–273.

Moschini, G., and R.J. Myers. 2002. "Testing for constant hedge ratios in commodity markets: a multivariate GARCH approach." *Journal of empirical finance* 9:589–603.

Ouyang, H., X. Wei, and Q. Wu. 2019. "Agricultural commodity futures prices prediction via long-and short-term time series network." *Journal of Applied Economics* 22:468–483.

Phillips, P.C., and P. Perron. 1988. "Testing for a unit root in time series regression." *Biometrika* 75:335–346.

Power, G.J., and C.G. Turvey. 2011. "Revealing the impact of index traders on commodity futures markets." *Applied Economics Letters* 18:621–626.

Said, S.E., and D.A. Dickey. 1984. "Testing for unit roots in autoregressive-moving average models of unknown order." *Biometrika* 71:599–607.

Samak, N., R. Hosni, and M. Kamal. 2020. "Relationship between spot and futures prices: The case of global food commodities." *African Journal of Food, Agriculture, Nutrition and Development* 20:15800–15820.

Sanders, D.R., and S.H. Irwin. 2015. "Bubbles, Froth, and Facts: What Evidence is there to Support the Masters Hypothesis?" Working paper, Department of Agricultural Consumer Economics, University of Illinois at Urbana-Champaign.

Sanjuán-López, A.I., and P.J. Dawson. 2017. "Volatility effects of index trading and spillovers on US agricultural futures markets: A multivariate GARCH approach." *Journal of agricultural economics* 68:822–838.

Shyy, G., V. Vijayraghavan, and B. Scott-Quinn. 1996. "A further investigation of the lead-lag relationship between the cash market and stock index futures market with the use of bid/ask quotes: The case of France." *The Journal of Futures Markets (1986-1998)* 16:405.

Thieu, L.Q. 2016. “Equation by equation estimation of the semi-diagonal BEKK model with covariates.” MPRA paper, No.75582, University Pierre and Marie Curie.

Tse, Y.K. 2000. “A test for constant correlations in a multivariate GARCH model.” *Journal of econometrics* 98:107–127.

Von Braun, J. 2007. *The world food situtation: new driving forces and required actions*. Intl Food Policy Res Inst.

Wu, F., W.L. Zhao, Q. Ji, and D. Zhang. 2020. “Dependency, centrality and dynamic networks for international commodity futures prices.” *International Review of Economics & Finance* 67:118–132.

Yang*, J., D.A. Bessler, and H.G. Fung. 2004. “The informational role of open interest in futures markets.” *Applied Economics Letters* 11:569–573.

Yang, J., and D.J. Leatham. 1999. “Price discovery in wheat futures markets.” *Journal of Agricultural and Applied Economics* 31:359–370.

Yip, P.S., R. Brooks, H.X. Do, and D.K. Nguyen. 2020. “Dynamic volatility spillover effects between oil and agricultural products.” *International Review of Financial Analysis*, pp. 101465.

Zhang, Y.J., Y. Fan, H.T. Tsai, and Y.M. Wei. 2008. “Spillover effect of US dollar exchange rate on oil prices.” *Journal of Policy Modeling* 30:973–991.

Zivot, E., and D.W.K. Andrews. 2002. “Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis.” *Journal of business & economic statistics* 20:25–44.

Zonghao, C. 2014. “Index Futures Trading, Spot Volatility and Market Efficiency.” *Journal of Management Sciences* 1:73–112.