Price Discovery and Volatility Spillover Effects: The Agricultural ETPS and Their Underlying Commodities

Yu Chen
South Dakota State University

PRICE DISCOVERY AND VOLATILITY SPILLOVER EFFECTS: THE AGRICULTURAL ETPS AND THEIR UNDERLYING COMMODITIES

BY

YU CHEN

A thesis submitted in partial fulfillment of the requirement for the degree

Master of Science

Major in Economics

South Dakota State University

2017

PRICE DISCOVERY AND VOLATILITY SPILLOVER EFFECTS: THE AGRICULTURAL ETPS AND THEIR UNDERLYING COMMODITIES

This thesis is approved as a creditable and independent investigation by a candidate for the Master of Science in Economics degree and is acceptable for meeting the thesis requirements for this degree. Acceptance of this thesis does not imply that the conclusions reached by the candidates are necessarily the conclusions of the major department.

Zhiguang Wang, Ph.D.
Thesis Advisor — Date

Eluned Jones, Ph.D.
Head, Department of Economics — Date

Dean, Graduate School — Date

ACKNOWLEDGEMENTS

I express my sincere gratitude to Dr. Zhiguang Wang as my advisor. Thanks for his help in extending my knowledge on the investment and research, and improving my skills and vision in this area, which benefits me greatly during my whole graduate life.

I would like to thank Dr. Lisa Elliott and Dr. Joseph Santos for their encouragement and suggestions to my thesis and coursework. Your comments always can help me make progress.

I would like to appreciate my fiancée, Shanshan Ma for supporting and encouraging me in the completion of this thesis. Also I am very grateful to my friend, Justin Price, Richard Mulder and Chad Te Slaa for their help with editing.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

PRICE DISCOVERY AND VOLATILITY SPILLOVER EFFECTS: THE AGRICULTURAL ETPS AND THEIR UNDERLYING COMMODITIES

YU CHEN

2017

This thesis investigates the price discovery and volatility spillover effects between agricultural ETPs and commodity underlying. We analyze historical prices of five most popular grain ETPs and their underlying commodities using VEC model and BEKK model. Price discovery is confirmed by bidirectional relationships between ETPs and underlying commodity in the long term, and the WEAT_ETP and CBOT Wheat Futures December Contracts. In addition, findings show unidirectional relationships between ETPs and underlying, mostly in the short term. In the process of price discovery, the information share of ETPs is much lower than that of underlying, with a potential downward trend. Volatility spillover is confirmed by bidirectional relationships between ETPs and underlying, such as JJG_ETP and soybean futures, and confirmed by unidirectional relationships, such as from wheat futures to DAG_ETP. For single commodity based ETPs, the degree of volatility spillover from the nearby futures contracts to ETPs is higher than that from distant futures contracts.

CHAPTER 1 INTRODUCTION

1.1 Background

Exchange Traded Products (ETPs) are a basket of securities, including stocks, bonds, commodities, or indices. There are three types of ETPs, such as Exchange Traded Funds (ETFs), Exchange Traded Notes (ETNs) and Exchange Traded Vehicles (ETVs). The main benefits of investments in ETPs are found through the ease of diversification, low expense ratios, tax efficiency, and transparency as well. This is combined with all the standard trading structures of equities (e.g., options, short selling, stop losses, and limit orders). ETPs can be bought and sold at any time during the trading day, in comparison to mutual funds that can only be sold at the end of the day when their net asset value (NAV) is calculated. Thus, in comparison to existing mutual funds or underlying securities, ETPs tend to be an attractive investment tool.

In recent years, ETPs markets have been dramatically growing, not only in terms of numbers and in terms of varieties of products, but also in terms of total assets and market values. Initially, these products aimed at replicating broad-based stock indices. New ETPs extended their fields to sectors, international markets, fixed-income instruments and lately commodities. During the first half of 2015, globally listed exchange traded products (ETPs) added $152 billion in net new assets, bringing total assets in the 11,295 listed funds to $2.971 trillion, which is almost half of the passive mutual fund industry. This drastic increase in value suggests that ETFs must have filled and continue to fill a gap in investors' needs.

With increasing capitalization, ETPs have been playing a significant role in the financial markets. However, it is the fact that ETPs are likely to be easily misused by investors, which might lead to liquidity and volatility issues. This may rely on the fact that ETPs are fairly new innovative financial products that a handful of investors, who are trading ETPs, actually do not have a deep understanding of differences from other financial derivatives in terms of investment strategies, complexities, latent risk, and regulations. For example, ETFs like DIA, SPY, and QQQ, are the top three most actively traded securities in the stock market. Due to clustering of volatility and the price discovery process, they are found to have the price deviation that exists during trading days (DeFusco et al. 2007). Also, in the futures market, price efficiency and volatility issues are a major concern after introducing new ETPs to the market.

1.2 Problem Identification

In the secondary market, ETPs, a sized asset of around $2.91 trillion, have been a considerable force that certainly impacts the movement of the whole market. Among ETPs, ETFs are dominating trading in the market. Recent related research has been focusing on three major topics: 1) exploring impacts of the arrival of ETFs on the underlying components, 2) examining the efficiency of index derivatives markets, and 3) investigating the price discovery of the index. Deville (2008) attempted to answer three major questions: 1) what impact does the advent of ETFs have on trading and market quality with regard to index component stocks and index derivatives, 2) do ETFs represent a performing alternative to conventional index funds, and 3) does the specific structure of ETFs allow for more efficient index fund pricing?

With regard to ETPs' impact on liquidity and volatility of securities, there is currently no consensus in the literature. Empirical research has particularly found that ETPs markets are likely to be more liquid and volatile than individual underlying securities, and thus have strong potential impact on individual securities. On the other hand, other research show that ETPs do not have a strong liquidity so that ETPs barely have interactive impacts on component securities due to information asymmetry and the lack of arbitrage opportunities in ETPs trading than individual stocks. (Park and Switzer 1995; Chou and Kugele 2006; Madura and Richie 2005).

Looking with multiple views of the impact from ETPs, researchers draw attention to price discovery and volatility spillover effects in order to have a deep understanding of the advent of ETPs era. Price discovery which is interpreted as 'the incorporation of the information implicit in investor trading into market prices' usually emphasizes the existence of information share. The information share associated with a specific market is defined as the proportion of the efficient price innovation variance that can be attributed to that market. Information share is likely to cause tracking errors or price deviations. This could explain why ETPs are traded at the premium or discount. Volatility spillover issues investigate how volatility in one market is transferrable to other markets through the arbitrage of goods between markets, which is usually distinguished temporarily, spatially, and vertically.

Price discovery and volatility spillover could happen in the same market, but for distinct securities, or for the same securities in different markets. For example, stocks in the Dow Jones Industrial Average, which are tradable in many stock exchanges, have been found to experience the existence of price discrepancy among different stock exchange markets. Also, the phenomenon of price discovery and volatility spillover could appear among related assets, but in a different market, such as commodity ETPs in the stock market and their underlying components in the commodity futures market.

Originally, the arrival of commodity ETPs was designed to enhance the diversification of the agricultural commodity index, and provide a more sophisticated strategy for investing in commodities than were provided by conventional commodity index. However, due to typical features such as cost saving, interest earned and transparency, they have attracted a host of active and aggressive investors, which leads to an increasing swing of liquidity among the futures market. Despite the importance of ETPs to the commodity futures market, it currently still has limited research on the arrival of agricultural ETPs. Thus far, research has found an existence of long-run co-integration between ETN prices and the values of their underlying commodity indexes (Noman et al. 2013). However, research has not been done on that examine the price discovery process and volatility spillover effect between commodity ETNs and their underlying.

It is interesting to note that the introduction of agricultural ETPs enriches investing activities for commodity investors, by the fact that traders can continuously trade ETPs instead of multiple commodity futures contracts, which includes a basket of commodity future contracts in the secondary market throughout trading days. In this case, an important question needs to be addressed: whether a volatile demand of ETPs will potentially lead to price movement and volatility spillover to their underlying securities or vice versa (i.e., the equity market vs. the commodity futures market)? In other words, it is reasonable to question that whether high volume of ETPs' trading would lead to high-frequency arbitrage activity that can transfer the price pressure from the ETPs market to the underlying securities, which results in the fact that the demand for ETPs would have a transmission demand effect for the underlying securities. Conversely, it is also worth considering the effect from underlying trading flows that would push a signal back to ETPs and probably influence the demand of ETPs shares. Therefore, this study aims at discovering the price discovery and volatility spillover effects between agricultural grain ETPs in the stock market and their underlying commodities in the futures market.

1.3 Research Objectives and Hypotheses

Objective

This study is to investigate bidirectional price discovery and volatility spillover effects between agricultural ETPs and their underlying commodities. In the first step, it is necessary to understand how liquidity of commodity futures in the commodity market could influence the liquidity of ETPs market, to uncover the existence of price discovery between both markets, and eventually to quantify the contribution of the price discovery from each market via the measure of information share. In the next step, if ETPs enables a channel of arbitrage trading, it is worth investigating whether the introduction of ETPs would cause volatility spillover effects among the ETP market and the markets of their underlying components.

Hypotheses

1) There is a bilateral relationship in the price discovery of agricultural ETPs and underlying, while the ETP market has a rising information share in the price discovery of the underlying commodities.

Two important issues related to price discovery are (a) to determine which market first incorporates new information about the underlying fundamental asset, and (b) how the efficacy of price discovery depends on market liquidity and the prevalence of asymmetric information. We use the information share (Hasbrouck 1995, Gonzalo and Granger 1995) to measure each market's contribution to the price discovery of the underlying commodities. According to previous research, it has been seen an existence of information share among indexes and their underlying. Therefore, in this study, we hypothesize that there is a significant and increasing amount of information share arising from the newly developed agricultural ETPs markets.

2) There is a bilateral volatility spillover effect between agricultural ETPs and their underlying commodities.

Volatility spillovers would happen within multiple related markets because most securities share common market information, have demand substitution effects on others, and compete in the usage of some common inputs, such as production materials and labor. When volatility in one market changes significantly, it leads to volatility movement in other relative markets. Yang, Zhang, and Leatham (2003) found the evidence of volatility transmission in the American and Canadian wheat market. Krause and Tse (2013) uncovered the bi-directional volatility transmission among five comparable broad markets and industry ETFs pairs in American and Canadian markets. Therefore, we hypothesize that there is a bi-lateral volatility spillover effect existing between agricultural ETPs and their underlying securities.

1.4 Justification of the Study

ETPs, typically index-based, consist of a basket of security assets. ETPs are therefore created to track the investment performance of specific indices. In that case, there is a theoretical relationship between ETPs and their underlying assets. This linkage is likely to depend on a rational expectation hypothesis, through which, investors measure ETPs' value as the net value of ETPs' underlying assets. With the changing of the net value of underlying securities, the value of ETPs fluctuate throughout the time. However, due to asymmetric information and arbitrage activities existing in the market, it is hard to track the net asset value of ETPs perfectly. Thus, to have a deep understanding of ETPs is necessary.

Studies on price discovery and volatility spillover effects in the financial market have shown multiple scenarios. They mostly focus on the relationships between liquid securities and industry indexes. Some of them is to investigate the price discovery and volatility transmission of same securities in different markets, while some is to uncover the relationships for different securities in the same market. However, price discovery and volatility transmission effects have rarely been studied among agricultural commodities and agricultural indexes. To my best knowledge, there are some insights of the price discovery between agricultural commodity futures and spot price. But I haven't seen quantified price discovery effects in the agriculture related paper, which will be applied in the paper using Hasbrouck's information share (1995). From that, we are able to capture the proportional contributions of each single market in the process of price discovery.

From a policy perspective, it is vital to understand the impacts that ETPs have had on the liquidity and volatility of commodity markets. If it is the case that ETPs are found to have direct influence on the volatility of underlying securities, it may be necessary for regulatory bodies to implement regulation to mitigate any potential effects. For example, if it is found that ETFs are negatively impacting market functionality, then policy response must focus on position limits, short-selling limits, and margin limits for ETFs.

This thesis is divided into five chapters. Chapter 1 describes the introduction, research objectives and the justification of the study. Chapter 2 presents a review of previous works related to price discovery and volatility spillover issues. Chapter 3 describes the data and research methodology used in the study. Chapter 4 presents and analyzes the empirical results of the study. Chapter 5 concludes the study.

CHAPTER 2 LITERATURE REVIEW

This section reviews literature related to price discovery and volatility spillover across multiple markets. With regard to the price discovery, it is divided into two sections. The first section illustrates the price discovery in non-commodity markets, such as stock index/ETPs and underlying stocks. The second section focuses on the price discovery process related to the commodity market, such as commodity index/ETPs and commodity futures. With regard to the volatility spillover, it includes two sections. The first section involves volatility spillover effects between the agriculture commodity futures market and the stock market. The second section illustrates previous studies of ETPs' impact on volatility.

2.1 Price Discovery

Price discovery in non-commodity markets

In general, price discovery is the process of determining an asset's full value through a marketplace at a given time. Within the process, it refers to two definition of values – observable price and unobservable price. The unobservable price reflects the fundamental value of security assets. It is different from the observable price, which can be broken down into its fundamental value and trading noise effects. Trading noise may come from stochastic price movements due to factors such as bid-ask spreads swing, inventory adjustments, and transient order imbalances.

Borkovec et al. (2010) conducted a study to discover linkages between exchange traded funds and the broader market, and a potentially severe mismatch in liquidity. In an attempt to answer the question on how does the liquidity provision affect price discovery for exchange traded funds, Borkovec et al. investigated price discovery of ETFs in a specific scenario: the U.S. financial markets on May 6th 2010. On this date, the market experienced an abnormal incline, lasting only a few minutes before recovering. This event is called a market flash crash. Their findings show that price discovery process failed for ETFs during the flash crash, which proximately results from an extreme slack of liquidity, both in ETFs and the relevant underlying components in the baskets. This might be a good explanation why it is unrealistic to believe that the value of ETFs was to some extent re-measured by market traders within a few minutes This resulted in a significant drop of investors' interest due to lack of depth, even though ETFs as a class of product have attracted liquidity interest in other periods.

Hasbrouck (1995) investigated Dow Jones 30 stocks, which are tradable in many stock exchanges, in order to discover price discrepancy and its mechanics among several markets for same individual stocks. In other words, it is to explore that whether there exists price discovery issues for one security that is trading in multiple markets. Hasbrouck adopts a microstructure model to assess co-integration of individual stocks in different markets, to determine how the information of stocks is transmitted among the different markets and where the information share is dominant. Using the VAR model and VEC model, Hasbrouck eventually shows that price discovery appears to be dominant in the NYSE market, and the information share of most Dow stocks is larger than the NYSE's market share (by trading volume).

Yan and Zivot (2002) summarized two types of price discovery measurements, including the information share (IS) and the component share (CS) between multiple markets. They adopted a structural cointegration model in order to clarify the application of IS and CS. The model applies two types of structural price shocks: a permanent news innovation to the common fundamental value, and a transitory liquidity/noise trading shock. In the findings, Yan and Zivot showed that information share (IS) and the component share (CS) are likely to be used together to distinguish the impacts of permanent and transitory shocks to stocks. This is because neither IS nor CS alone can fully explain the price discovery dynamics between multiple markets. In other words, the component share cannot be interpreted as a market's price responses to shocks, and the information share failed to present the dynamics even when the cross-market innovations are uncorrelated.

Henker & Marte (2006) attempted to contradict previous predictions that the futures contract leads the index in the process of price discovery. They explored information share between the security basket (HOLDR) and its portfolio (underlying components), and eventually found out that the price of the portfolio of underlying securities is more informative and leads the HOLDR (basket) price. This output is supportive of the theoretical study by Subrahmanyam (1991), in which it is predicted that nonsynchronous trading in the underlying components of an index may enlarge the probability of the lead that the index net asset value surpasses its market price, and that the lead from the portfolio to the basket is larger than that from the basket to the portfolio.

Due to the feature of intraday freedom-to-trade, ETPs' prices are supposed to fluctuate over the trading day, and its price will probably either be at a premium or discount from the NAV. To clarify, if shares of an ETP trade at a discount below the net value of the index's underlying shares, the investor can long a host of ETP shares and short its underlying components. In this case, price discrepancy of ETPs is hardly avoidable. Aber et al. (2009) conducted a study on price volatility and tracking ability of ETFs, showing that ETFs, when their daily prices appear to be volatile, have more possibility to trade at a premium to their net asset value than at a discount, implying that the market tended to overvalue these ETFs compared to their underlying NAVs. In addition, they stress that both trading types have similar co-movement with their benchmarks, but are slightly distinguished in terms of their tracking ability.

Due to regular management of ETPs, like formal creation and redemption, price deviations are likely to appear. This is called a relative performance weakness by Gastineau (2004). In the event of the mispricing of ETPs, investment arbitrage usually comes along with price tracking errors. DeFusco et al. (2011) evaluated the pricing deviations of the three most liquid ETFs, Spider, Diamonds and Cubes, from the price of the underlying index by using the GARCH model. The conclusion was that the pricing deviation is predictable due to its stationarity, series of volatility and lead-lag relationship. These deviations are to be considered as additional costs for the ETFs.

In addition, Engle and Sarkar (2006) ever doubted that measurements of premiums or discounts of ETFs in most models can be misleading because the net asset value of ETFs' underlying components is not correctly illustrated or because the price of ETFs is inaccurately tracked. They attempted to introduce a new model, called the errors-in-variables model. This model measures the standard deviation of the remaining pricing errors and investigates the time variation in this standard deviation. Through the use of the Kalman Filter State Space model, the 'dyna' model, and the GARCH model, Engle and Sarkar eventually discover that the premiums (discounts) for the domestic ETFs, which is typically slander and transitory, usually lasts only a few minutes. The standard deviation of the premiums (discounts) is 15 basis points on average across all domestic ETFs, which is considerably lower than the bid-ask spread. Meanwhile, premiums (discounts) of international ETFs are much larger and last longer up to a few days. The reason for this difference is explained by the higher cost and the complexity of the creation and redemption of international ETFs. The bid-ask spreads are also much wider but are comparable with the standard deviation of the premiums.

Price Discovery in Commodity Market

In the commodity futures market, price discovery is also a major issue. Agriculture companies are highly involved in the process of producing and commercializing in which information is generated and transferred into the market. In this process, it is not likely to guarantee that information is appropriately interpreted and used, which to some extent cause price deviation in the markets.

To improve our understanding of relative pricing efficiency on futures markets for wheat, Yang and Leatham (1999) adopting the ECM, examined the dynamic-price discovery mechanism in three wheat futures markets. The study states the prices of KCBT were found to drive the price changes in both CBT and MGE in the long run. In the short run, KCBT and CBT contributed more to the price information transmission for a longer time while MGE was limited to a shorter time horizon. These findings were explainable by the market microstructure of the three futures markets, including the role of underlying cash wheat, market size, and speculation level.

Figuerola-Ferretti et al. (2010) demonstrated and measured the phenomenon of price discovery in both futures markets and spot markets, adopting the two types of price discovery processing created by Garbade and Silber (1983). These price discovery processes combined with the method of permanent Transitory decomposition by Gonzalo and Granger (1995), eventually illustrate an equilibrium model of price dynamics between futures markets and spot markets with finite elasticity of arbitrage services and convenience yields. Their findings demonstrate that the linear relationship in futures and spot markets depends on the elasticity of arbitrage services and is determined by the relative liquidity traded in the spot and futures markets. Also, after testing non-ferrous metals prices (Al, Cu, Ni, Pb, Zn) traded in the London Metal Exchange (LME), Figuerola-Ferretti et al. discovered backwardation is very common in most of the markets, and in those highly liquid futures markets (Al, Cu, Ni, Zn), futures prices are typically information dominant.

Storage is regarded as an economic force that connects the futures and cash market in terms of commodity. Through storage, arbitrage might easily work. To explore the tie of price discovery and commodity storage, Yang et al. (2002) examined the price discovery performance of storable and non-storable commodities in the futures markets. Assuming a perfect storable commodity model exists, which does not cause arbitrage, their findings show that asset storability does not have a significant impact on the existing co-integration between cash price and futures prices for agriculture commodities. Asset storability also does not change the function of the futures market in predicting cash prices in the long run, but it does, to some extent, impact the variance of futures markets' prediction.

Index funds have been increasingly flowing into commodity futures markets over the last decade, which, in principle, could have influence on the risk premium of the commodity future contract through a large amount of buying. To have a deep understanding of it, Hamilton and Wu (2013) attempted to look for a systematic relationship between the expected returns of futures contracts and the net value of commodity futures contracts held by index-fund traders using a simple regression model. After testing 12 agricultural commodities, they found that it is not significant that the investors' positions of agricultural contracts possibly facilitate to predict returns on the near futures contracts. In the oil futures market, their findings, under Singleton's method, showed some support of binary relation in the earlier data, especially in the recession of 2007-2009.

2.2 Volatility Spillover

Volatility spillover within Agriculture Markets

Volatility spillover is the idea that volatility in one market could transmit to other markets, via sharing market information and the arbitrage of goods between markets. In the financial market, many questions related to volatility spillover have often been asked and investigated. Does the volatility of a major market lead to the volatility of other markets? Does the volatility of an asset transmit or spillover to another asset directly or indirectly through its conditional covariance? Do the innovations or the shocks from one market increase the volatility in another market, and are the impacts the same for negative and positive shocks?

Volatility spillovers exist among agricultural commodity markets because most commodities share common market information, have demand substitution effects on others, and compete in the usage of some common inputs, such as production materials and labor. When volatility in one market changes significantly, it leads to volatility swings in other relative markets. Such uncertainty and risks in the commodity market highly impact production and marketing decisions for market participants.

In this case, research on volatility spillovers in agricultural commodity markets has become an important issue. Researchers focus on an investigation of overall market behaviors, and an exploration of the transmission of risks and shocks across interrelated markets. To achieve such goals, it requires a recognition of linkages between different markets and, in particular, the mechanism of volatility transmission among them. Also, the dynamics of linkages are important indicators to help understand overall market behavior and performance.

Yang, Zhang, and Leatham (2003), to discovery futures price and volatility transmissions in the wheat market, conducted a study based on three wheat production regions. These included the United States (US), Canada, and the European Union (EU). Using a specific multivariate GARCH model (BEKK), their findings show that the volatility of the EU market is self-dependent, but somehow has been able to transmit to the U.S. and Canadian markets, but not vice versa. In addition, in the U.S., the volatility in wheat prices is affected by Canadian markets, but not vice versa, which is interpreted as Canada having the dominant role in the wheat market.

Buguk et al. (2003) conducted a study to examine whether the transmission of volatility exists within a vertical catfish supply chain, knowing this phenomenon occurs in the financial markets. They questioned whether price volatility in input markets (feeding materials: corn, soybeans, menhaden) could transmit itself through higher market levels (catfish feed and farm- and wholesale-level catfish), and vice versa. An exponential GARCH (or EGARCH) model was used to capture possible spillovers among price series, assuming a unidirectional transmission between feeding material and other market levels according to the size of the catfish and feed markets relative to the corn and soybean markets. In their results, they illustrate that there is a significant unidirectional spillover between corn, soybean, menhaden prices, and catfish prices (feed, farm, and wholesale-level fish prices), which provides evidence of volatility spillovers existing in an agricultural market.

Zhao and Goodwin (2011), to investigate the topic of volatility spillovers, examined relationships and transmissions among implied volatilities that are derived from two options markets – corn and soybeans. They, using weekly average data from 2003 to 2010, applied a VAR model with Fourier seasonal components as exogenous variables, impulse response functions, and bootstrapped Chow tests. Their findings indicated that volatility spillovers exist from the corn market to the soybean market, but not from the soybean market to the corn market. In addition, from impulse response functions, they discovered that responses of implied volatility in one market are positive and highly significant to a shock in itself.

Du, Yu, and Hayes (2011) examined the roles of various factors influencing the volatility of crude oil prices and the possible linkage between this volatility and agricultural commodity markets (specifically corn and wheat). They applied a bivariate stochastic volatility model to estimate three pairs of log returns of weekly crude oil, corn, and wheat futures prices from November 1998 to January 2009. The model parameters are estimated by the Bayesian Markov chain Monte Carlo methods. In their findings, Du, Yu, and Hayes displayed evidence of volatility spillover among crude oil, corn, and wheat markets after the fall of 2006. This could be largely explained by the tightened interdependent relationships between markets, which is induced by ethanol production.

Serra and Gil (2012) studied the U.S. corn price fluctuations of the past two decades to determine whether stock building can mitigate price fluctuations in a volatile food market. They discovered that corn price volatility can be explained by the clustering influence from energy prices, corn stocks, and the global economic conditions. A multivariate GARCH specification that allows for exogenous variables in the conditional covariance model is estimated both parametrically and semi parametrically. In the findings, Serra and Gil showed that (1) there exists price volatility transmission between ethanol and corn markets; (2) macroeconomic instability can increase corn price volatility; (3) stock building is found to significantly reduce corn price fluctuations.

Volatility Spillover Related to ETPs market

The invention of ETPs is regarded as one of the most successful financial innovations in the past twenty years. This kind of security portfolio gives the ability to track the performance of the broad-base stock index. At the present, a handful of studies are devoted to investigate the effects of ETPs arrival to the market. Researchers attempt to answer a few questions: what impacts it has after introducing ETPs into the market and how ETPs influence the liquidity of their underlying components? Among those topics, most of them emphasize the examination of volatility effects from ETPs.

With ever increasing liquidity and arbitrage opportunities, ETFs have attracted a handful of noise traders. This noise could be translated into underlying components through the arbitrage channel, which contributes to the liquidity of underlying securities. Ben-David et al. (2014) explored whether ETFs increase the non-fundamental volatility of the underlying securities, using OLS regression and a regression discontinuity. Their output displays that ETFs propagate to introduce new noise into the market, as opposed to remodeling the existing noise, and stocks with higher ETF ownerships present substantially higher volatility. More interestingly, they state that ETFs ownership presents a significant relation with movement of component stock prices from a random walk at the intraday and daily frequencies.

Krause and Tse (2013) conducted a study on how information flows across broad market and industry ETFs in Canada and the United States, by examining the existence of price discovery and volatility transmission among five comparable broad markets and industry ETFs pairs in each market. Using the VAR model and EGARCH model, they discover that volatility transmissions between the U.S. market and Canadian market are highly bi-directional, while price discovery flows are consistently dominant from the U.S. market to the Canadian market among ETFs. Also, information is captured more quickly into prices through traded securities in the U.S. market, and the combination of negative U.S. return spillovers and asymmetric volatility. This creates bilateral volatility spillover effects.

Corbet and Twomey (2014) generated questions of whether commodity ETFs amplify or influence volatility in the period after their introduction into international commodity markets. In other words, does volatility effects from commodity ETFs act as an accelerant for price deviation, or as a mechanism for liquidity improvements, thereby expediting information transmission? Furthermore, given volatility effects exist prominently, Corbet and Twomey continue to question whether the size of ownership of the commodity among ETFs matters with effects. Using the EGARCH model, they found out that larger market-proportional ETF holdings present higher volatility than smaller ETF holdings, while smaller commodity markets, such as agriculture grain commodity, are found to have growing liquidity flows, resulting from ETFs activities.

Lin and Chiang (2005) conducted a study to investigate volatility swings of underling securities of the Taiwan 50 Index after the arrival of its ETF, named TTT. Following a method that uses the unconditional variance of a GARCH model as the volatility of underlying components of the Taiwan 50 Index, they demonstrated that the volatility of the component stocks rise up after introducing TTT into the market. The magnitude of volatility movement is not statistically distinguishable within most stock sectors, but is in the electronic and the financial sector. In these sectors, the volatility of TTT underlying companies increased dramatically after the advent of TTT. More interestingly, it also displayed that the volatility of several companies in the mixed sector are reduced to some extent.

CHAPTER 3 DATA AND METHODOLODY

3.1 Data Description

This study selects 5 typical ETPs of grain commodities with comparably higher trading volumes, including Teucrium Corn Fund (CORN), Teucrium Soybean Fund (SOYB), Teucrium Wheat Fund (WEAT), iPath Bloomberg Grains Subindex Total Return ETN (JJG), PowerShares DB Agriculture Double Long ETN (DAG). Each ETP comprises of several commodity futures underlying components, or tracking certain grain index which comprises a basket of commodities futures.

The CORN's net asset value (NAV) reflects the daily changes in percentage terms of a weighted average of the closing settlement prices for three futures contracts of corn commodity ("Corn Futures Contracts") that are traded on the Chicago Board of Trade ("CBOT"). Specifically, CORN comprises of three different Corn Futures Contracts: (1) the second-to-expire CBOT Corn Futures Contract (C1), weighted 35%, (2) the third-to-expire CBOT Corn Futures Contract (C2), weighted 30%, and (3) the CBOT Corn Futures Contract expiring in the December following the expiration month of the third-to-expire contract (C3), weighted 35%. (This weighted average of the three referenced Corn Futures Contracts is referred to herein as the "Benchmark".) Each contract is expected to roll over in its last trading day.

Similarly, SOYB's NAV is tracked by Soybean Futures Contracts Benchmark. Specifically, the SOYB comprises of three different Soybean Futures Contracts: (1) second-to-expire CBOT Soybean Futures Contract (S1), weighted 35%, (2) the third-to-expire CBOT Soybean Futures Contract (S2), weighted 30%, and (3) the CBOT Soybean

Futures Contract expiring in the November following the expiration month of the third-to-expire contract (S3), weighted 35%. Each contract is expected to roll over in its last trading day.

Similarly, WEAT's NAV is calculated by Wheat Futures Contracts Benchmark. Specifically, the WEAT comprises of three different Wheat Futures Contracts: (1) the second-to-expire CBOT Wheat Futures Contract (W1), weighted 35%, (2) the third-to-expire CBOT Wheat Futures Contract (W2), weighted 30%, and (3) the CBOT Wheat Futures Contract expiring in the December following the expiration month of the third-to-expire contract (W3), weighted 35%. Each contract is expected to roll over in its last trading day.

Additionally, JJG tracks the performance of Bloomberg Grains Subindex Total Return℠ (the "Grains ETNs"), which includes Corn Futures Contracts (42.71%), Soybean Futures Contracts (32.49%), Chicago Wheat Futures Contracts (Cwheat) (18.24%), and Kansas City Wheat Futures Contracts (Kwheat) (6.55%), whose weights are timely floating. To minimize tracking errors, the Bloomberg Grains Subindex approaches a typical way for rolling over commodity contracts, which counts on Lead Futures Contracts (front month contracts) starting from 100% and reducing by 20% on each trading day, and Next Futures Contracts (second month contracts), starting from 0% amount and rising by 20% on each trading day, this process happens from 6th business day to 10th business day in each rolling month.

Also, DAG tracks the performance of a total return version of the Deutsche Bank Liquid Commodity Index – Optimum Yield Agriculture™ (the "Index"). The return on the Index is derived by combining the returns on two component indices: the DB 3-Month T-

Bill Index (the “TBill index”) and the Deutsche Bank Liquid Commodity Index – Optimum Yield Agriculture™ Excess Return (the “agriculture index”). The agriculture index is intending to reflect the price changes, positive or negative, with a basket of four agricultural commodities futures contracts: corn (weighted 25%), soybeans (weighted 25%), wheat (weighted 25%), and sugar (weighted 25%). After the close of trading on February 16, 2012 (the "Effective Date"), one of underlying components in the agriculture index, wheat futures contract, which was traded on the Board of Trade of the City of Chicago, Inc. (“CBOT”), was replaced by a basket of three underlying futures contracts on wheat that are traded on CBOT, the Kansas City Board of Trade (“KCBT”) and the Minneapolis Grain Exchange, Inc. (“MGEX”), respectively. These contracts are weighted equally on each rebalancing day, about 8.33% respectively. But to ensure the consensus of data, this study still consider the factor of wheat futures contracts as previous as the CBOT wheat futures. To avoid tracking error in the rolling month, the agriculture index approaches a typical method to roll over each contract like Bloomberg Grains Subindex, adopting Lead Futures Contracts and Next Futures Contracts changing with an amount of percentage, which starts from 2nd business days to 6th business day in months prior to each contract expiration month.

In fact, the newly developed agricultural ETPs haven’t a long trading history. This study will use all of their trading history by March 14th 2016, associated with their underlying components. Among them, JJG has the longest trading history (October 23rd, 2007), then DAG (April 15th, 2008), CORN (June 8th, 2010), WEAT (September 19th, 2011), and SOYB (September 19th, 2011). Historical data of each ETP is obtained from Yahoo Finance, while historical data of ETPs’ underlying is gained from Quandl Database. To ensure the tracking accuracy, all the daily data of underlying securities are manipulated according to the ETPs' issuing prospects. To conduct this study, daily price of each security is used.

3.2 Tests of Stationarity and Cointegration

If the stochastic data is non-stationary, the method of OLS would yield invalid estimates, such as yielding high R square values and high t-ratios. This is called 'spurious regression'. In order to prevent the disturbance of non-stationary data, it is necessary to test the stationarity of the data sample in the beginning. Two methods are implemented to test the stationarity of the data: the Augmented Dickey-Fuller (ADF) test and the Phillip and Perron (PP) test. The ADF test is an augmented version of the Dickey–Fuller test for a more complex time series models, allowing autocorrelation at higher order lags. The null hypothesis of an ADF test is that there is a unit root in time series data samples. The Phillips Perron test that builds on the Dickey–Fuller test of null hypothesis is helpful to test the unit root among variables that has a high order of autocorrelation.

Then, the Johansen test, regarded as a multivariate generalization of the augmented Dickey-Fuller test, is commonly used to test cointegrated relationships between variables. The Johansen tests are likelihood-ratio tests that include maximum eigenvalue test and the trace test. Because of this, the Johansen test permits to track more than one cointegrated relationship when there are more than two variables.

3.3 Models

The main purpose of the research is to examine the existence of price discovery between grain commodity ETPs and their underlying components which are trading in the stock market and futures market, and to explore the volatility spillover effect among those securities in different financial markets. To achieve this goal, this study will adopt the Vector Error Correction Model (VECM) to discover the short-term and long-term relationship between ETPs and their underlying. Based on that, this study then will apply the mechanism of information share by Hasbrouck (1995), in order to quantify the value of price discovery. Lastly, we will conduct the Baba, Engle, Kraft, and Kroner (BEKK) model to examine shock and volatility transmission effects among them.

3.3.1 Vector Error Correction Model

Vector Error Correction Model (VECM) is commonly used with nonstationary series that have a long-run stochastic trend, known as cointegration. To specify, the VECM restricts the cointegrated relationships of the long-run behavior of the endogenous variables, instead it captures a cointegration term that allows a wide range of short-run dynamics. The cointegration term, known as the error correction term relates to last-periods deviation from a long-run equilibrium, has influences on its short-run dynamics.

VECM is a representation of Vector Autoregression (VAR) Model, which assumes that innovations are normally distributed. Firstly, we consider k variates and i^{th} order vector autoregressive time series, $Y_t = \left[Y_{1,t} \ldots Y_{k,t} \right]'$ and VAR model as follow,

$$Y_t = C + \Pi_1 Y_{t-1} + \ldots \Pi_k Y_{t-i} + \varepsilon_t \tag{1}$$

Where $t = 1, 2..., n$, and C is the constant term. The error term ε_t is assumed to be k-dimensional normally distributed $N(0,\Omega)$, where Ω is the covariance matrix of the error term. After introducing a $k \times k$ matrix Π which defined as

$$\Pi = \Pi_1 + ...\Pi_k - I \tag{2}$$

We reformat VAR model as a VEC model,

$$\Delta Y_t = C + \Pi Y_{t-1} + \sum \Theta_i \Delta Y_{t-i} + \varepsilon_t \tag{3}$$

Or,

$$\begin{bmatrix} \Delta Y_{1t} \\ . \\ . \\ \Delta Y_{kt} \end{bmatrix} = C + \begin{bmatrix} \varphi_{11} & . & . & \varphi_{1k} \\ . & . & . & . \\ . & . & . & . \\ \varphi_{k1} & . & . & \varphi_{kk} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ . \\ . \\ Y_{k,t-1} \end{bmatrix} + \Sigma \begin{bmatrix} \phi_{11} & . & . & \phi_{1k} \\ . & . & . & . \\ . & . & . & . \\ \phi_{k1} & . & . & \phi_{kk} \end{bmatrix} \begin{bmatrix} \Delta Y_{1,t-i} \\ . \\ . \\ \Delta Y_{k,t-i} \end{bmatrix} + \varepsilon_t \tag{4}$$

Where $C = (C_1, C_2, C_3, ...C_k)'$ is a $k \times 1$ vector of intercept terms, $\Pi = \Pi_1 + ...\Pi_k - I$ is a $k \times k$ coefficient matrices, which illustrate the long run relationship, $\Theta_i = -(\Pi_{i+1} + ...\Pi_p), i = 1,..p-1.$, is a $k \times k$ coefficient matrices of ΔY_{t-i}, which states the short-term relationship, $\Delta Y_{t-i} = (\Delta Y_{1t-i}, \Delta Y_{2t-i}, \Delta Y_{3t-i}, ..., \Delta Y_{kt-i})'$ is a $k \times 1$ vector of cointegrating factor, which t =1, ε_t is a $k \times 1$ vector of residuals.

From (3), this study investigates the significance of both long-run and shot-run parameters to examine the price discovery effect of the mean returns between each agricultural ETP and their underlying components. If coefficients related to ETPs in the off-diagonal of the matrix Π are found to have a statistical significance, it means there are price spillover effects existing between the ETP and its underlying components in the long run. For example, if the model finds the significance of the φ_{ik} parameters between an underlying (i) and an ETP (k) for the sampled data, we can say price spillover effects are found running from agricultural ETPs to underlying commodity in the long run, and vice versa. Similarly, if coefficients related to ETPs in the off-diagonal of the matrix $\sum\Theta_i$ are found to have a statistical significance, it means there are price spillover effects existing between the ETP and its underlying components in the short run. For example, if the model finds the significance of the ϕ_{ik} parameters between an underlying (i) and an ETP (k) for the sampled data, we can say price spillover effects is found running from agricultural ETPs to underlying commodity in the short run, and vice versa. Meanwhile, the residual ε_t will be collected and used for analyzing volatility spillover effects by Baba, Engle, Kraft, and Kroner model in the next step.

3.3.2 Information Share

Hasbrouck (1995) proposes a measurement for one market's contribution to price discovery based on the share of the variance of innovation that attributes to this market. From the VEC model, Hasbrouck assumes that the "efficient price" of securities follows a random walk and has the permanent component. Then, the information share decomposes the variance of efficient price changes into components attributable to the different markets. To compute the information share, the price changes are assumed to be covariance stationary. This implies that they may be expressed as the vector moving average (VMA)

$$\Delta Y_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \dots \qquad (5)$$

Where ε_t is a zero-mean vector of serially uncorrelated residual with the covariance matrix Ω, and ϕ_i (i = 1, 2...p-1) coefficients are the impulse response parameters. The cumulative impulse response function is

$$M_k = \Sigma_{i=0}^{k} \phi_i \tag{6}$$

Where $M = \lim_{k \to \infty} M_k$. The rows of M are all identical. Let m be any row of M . So the random-walk component of the prices is:

$$w_k = m\varepsilon_t \tag{7}$$

So the innovation variance is:

$$\sigma_w^2 = m\Omega m^{'} \tag{8}$$

If Ω is diagonal, which means the market innovations are uncorrelated, then $m\Omega m^{'}$ will consist of k terms, each of which represents the contribution to the random-walk innovation from a particular market. Then, the information share of the jth market is defined as

$$IS_j = \frac{m_j^2 \Omega_{jj}}{m\Omega m^{'}} \tag{9}$$

If Ω is not diagonal, which means the market innovations are correlated, the measurement of information share has the problem of attributing the covariance terms to each market. To avoid this problem, Hasbrouck (1995) suggests to calculate the Cholesky decomposition of Ω and measure the information share using the orthogonalized innovations. According to Hasbrouck (1995), the orthogonal innovation matrix contains the upper and lower bounds, which are very close, generally within 0.001 of each other. To be brief, this study only reports the lower bound in the analysis, since results using the upper bound are virtually identical. Thus, Let F be a lower triangular matrix such that $\Omega = FF^{'}$. Then the information share of the jth market is defined as

$$IS_j = \frac{([mF]_j)^2}{m\Omega m^{'}} \tag{10}$$

Where $[mF]_j$ is the jth element of the row matrix mF .

The information share is a relative proportion of contribution that attributes to different securities. It measures which security presents more informative values and moves first in response to new information. For instance, if the information share of an ETP is higher than that of its underlying components, we can say the ETP will move first when responding to new innovation and there is more price discovery in the ETP, and vice versa.

3.3.3 Baba, Engle, Kraft, and Kroner model

Baba, Engle, Kraft, and Kroner (BEKK) model, which is a class of Multivariate GARCH model, is proposed by Engle and Kroner (1995) for investigating volatility spillovers effects. The BEKK model allows for volatility spillover across multiple markets. To achieve that goal, this method ensures the condition of a positive-definite conditional variance-covariance matrix in the process of optimization.

In this study, the BEKK model is adopted to provide an appropriate path for exploring the volatility transmission linkage between multiple securities that are trading in different markets. In this model, we assume that variables have constant correlation and innovations follow a Student's t distribution with v degrees of freedom. Below is a multi-dimensional BEKK parameterization of our data series:

$$\mathrm{H}_t = CC^{'} + \mathrm{A}\Psi\mathrm{A}^{'} + \mathrm{B}\mathrm{H}_{t-1}\mathrm{B}^{'} \tag{11}$$

Where, $H_t = \begin{bmatrix} \sigma_{11,t} & . & . & \sigma_{1k,t} \\ . & . & & . \\ . & & . & . \\ \sigma_{k1,t} & & & \sigma_{kk,t} \end{bmatrix}$; $C = \begin{bmatrix} C_{11} & . & . & C_{1k} \\ . & . & & . \\ . & & . & . \\ C_{k1} & . & . & C_{kk} \end{bmatrix}$ is an upper triangular matrix;

$A = \begin{bmatrix} \alpha_{11} & . & . & \alpha_{1k} \\ . & . & & . \\ . & & . & . \\ \alpha_{k1} & . & . & \alpha_{kk} \end{bmatrix}$, is $k \times k$ coefficient matrices; $\Psi = \begin{bmatrix} \varepsilon_{1,t-1}^2 & . & . & \varepsilon_{1,t-1}\varepsilon_{k,t-1} \\ . & . & & . \\ . & & . & . \\ \varepsilon_{k,t-1}\varepsilon_{1,t-1} & . & . & \varepsilon_{k,t-1}^2 \end{bmatrix}$;

$B = \begin{bmatrix} \beta_{11} & . & . & \beta_{1k} \\ . & . & & . \\ . & & . & . \\ \beta_{k1} & . & . & \beta_{kk} \end{bmatrix}$, is $k \times k$ coefficient matrices; $H_{t-1} = \begin{bmatrix} \sigma_{11,t-1} & . & . & \sigma_{1k,t-1} \\ . & . & & . \\ . & & . & . \\ \sigma_{k1,t-1} & . & . & \sigma_{kk,t-1} \end{bmatrix}$;

Or,

$$\begin{bmatrix} \sigma_{11,t} & . & . & \sigma_{1k,t} \\ . & . & & . \\ . & & . & . \\ \sigma_{k1,t} & & & \sigma_{kk,t} \end{bmatrix} = \begin{bmatrix} C_{11} & . & . & C_{1k} \\ . & . & & . \\ . & & . & . \\ C_{k1} & . & . & C_{kk} \end{bmatrix} + \begin{bmatrix} \alpha_{11} & . & . & \alpha_{1k} \\ . & . & & . \\ . & & . & . \\ \alpha_{k1} & . & . & \alpha_{kk} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1}^2 & . & . & \varepsilon_{1,t-1}\varepsilon_{k,t-1} \\ . & . & & . \\ . & & . & . \\ \varepsilon_{k,t-1}\varepsilon_{1,t-1} & . & . & \varepsilon_{k,t-1}^2 \end{bmatrix} \begin{bmatrix} \alpha_{11} & . & . & \alpha_{k1} \\ . & . & & . \\ . & & . & . \\ \alpha_{1k} & . & . & \alpha_{kk} \end{bmatrix} + \tag{12}$$
$$\begin{bmatrix} \beta_{11} & . & . & \beta_{1k} \\ . & . & & . \\ . & & . & . \\ \beta_{k1} & . & . & \beta_{kk} \end{bmatrix} \begin{bmatrix} \sigma_{11,t-1} & . & . & \sigma_{1k,t-1} \\ . & . & & . \\ . & & . & . \\ \sigma_{k1,t-1} & . & . & \sigma_{kk,t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & . & . & \beta_{k1} \\ . & . & & . \\ . & & . & . \\ \beta_{1k} & . & . & \beta_{kk} \end{bmatrix}$$

In matrix A, the diagonal elements, depict the ARCH effect, measure the impact of shocks on securities' own volatility, and the off-diagonal elements illustrate spillover effects from other securities' shock. The coefficient α_{ij} (i=1, 2…k; j=1, 2...k), given its statistical significance, for example, presents a cross effect running from the lagged residual terms of the security i to the security j and vice versa. In this study, each ETP is placed in the last subsequence in each model. If the coefficient α_{kj} is related to an ETP, say security k is an ETP and security j is an underlying for example, we could interpret that a shock from the ETP has an important impact on the underlying, and vice versa.

In matrix B, the diagonal elements, depict the GARCH effect, measure each security's past volatility effect on its conditional variance, and the off-diagonal elements captures the spillover effects from other securities' the past volatility movement. The coefficient β_{ij} (i=1, 2...k; j=1, 2...k), presents a cross-effect running from of the past volatility movement of security i to the current volatility of security j, and vice versa. In this study, each ETP is placed as the last variable in each model. If the coefficient β_{kj} is related to an ETP, say security k is an ETP and security j is an underlying, we could interpret that the past volatility movement from the ETP has an important spillover effect on the volatility of underlying, and vice versa.

To measure the magnitude of volatility spillovers, the squared summation of the cross terms of the BEKK model $\alpha_{ij}^2 + \beta_{ij}^2$ (i=1, 2...k; j=1, 2...k) is adopted. If the coefficients α_{kj} and β_{kj} are statistically significant, say security k is an ETP and security j is an underlying, we can say the expression $\alpha_{kj}^2 + \beta_{kj}^2$ measures the magnitude of volatility spillover from the agricultural ETP (k) to the underlying (j), and vice versa. The difference in magnitudes of volatility spillovers helps to identify the rank of contribution of volatility from underlying to an ETP. And the difference in magnitudes of volatility spillovers helps to identify the rank of contribution of volatility from an ETP to underlying. Due to the different scales of price of ETPs and underlying, it is difficult to compare the magnitudes of volatility spillovers from both sides. Therefore, in this study, we only aim to ranking the contribution from one market to the other market.

CHAPTER 4 RESULT ANALYSIS

4.1 Summary Statistics

This paper examines the price discovery and volatility spillover effects between grain commodity ETPs and their underlying components. To achieve this goal, this study includes 5 ETPs. Some of them are specialized funds, which comprise a single type of agricultural commodity futures, but different contract months, such as CORN, WEAT and SOYB. Some are mixed funds, which comprise different types of agricultural commodity futures, such as JJG and DAG. As the history of agricultural ETPs is not too long, this study covers all of daily data for each fund since their inception dates. Specifically, CORN and their underlying are starting from 06/08/2010-03/14/2016, WEAT and their underlying are starting from 09/19/2011-03/14/2016, SOYB and their underlying are starting from 09/19/2011-03/14/2016, JJG and their underlying are starting from 10/23/2007-03/14/2016, and DAG and their underlying are starting from 04/15/2008-03/14/2016. Figure 4.1 graphs historical price of CORN_ETP and its underlying, C1, C2 and C3. Figure 4.2 graphs historical price of WEAT_ETP and its underlying, W1, W2 and W3. Figure 4.3 graphs historical price of SOYB_ETP and its underlying, S1, S2 and S3. Figure 4.4 graphs historical price of JJG_ETP and its underlying, corn futures, soybean futures, Cwheat futures and Kwheat futures. Figure 4.5 graphs historical price of DAG_ETP and its underlying, corn futures, wheat futures, soybean futures and sugar futures. The price history of selected ETPs and their underlying is shown in Figures 4.1-4.5. Descriptive summary of historical price data is reported in Table 4.1.

Figure 4.1: Historical price of CORN_ETP and underlying

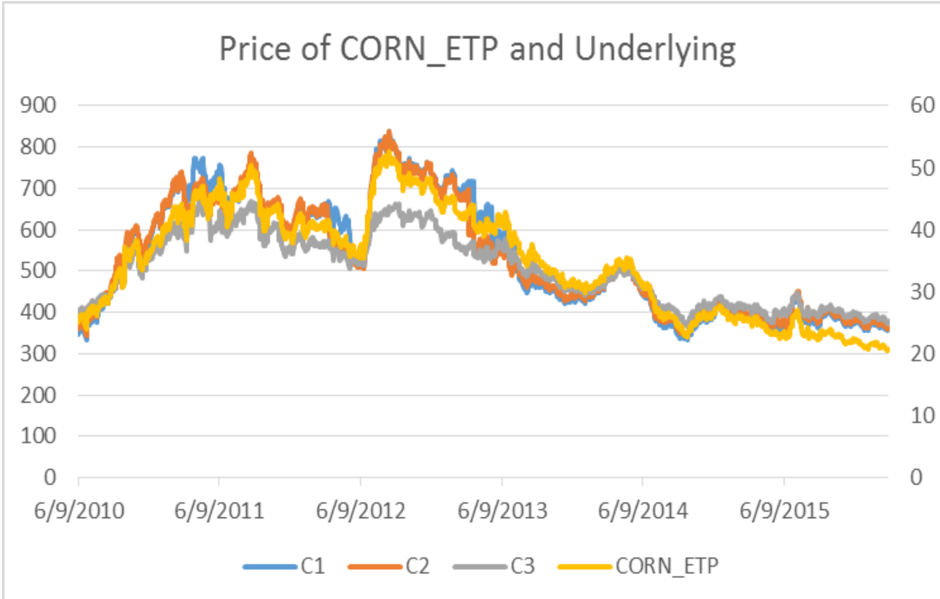


Figure 4.2：Historical price of WEAT_ETP and underlying

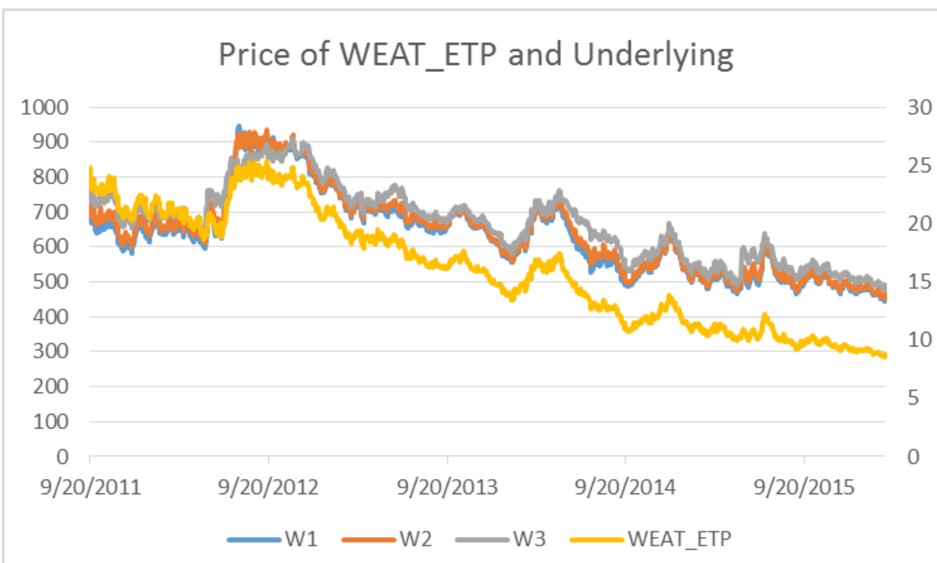


Figure 4.3: Historical price of SOYB_ETP and underlying

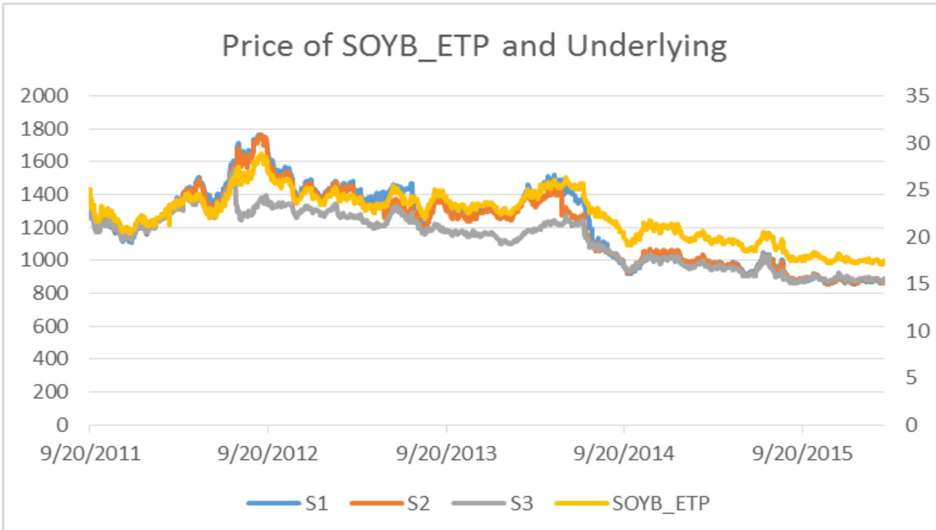


Figure 4.4: Historical price of JJG_ETP and underlying

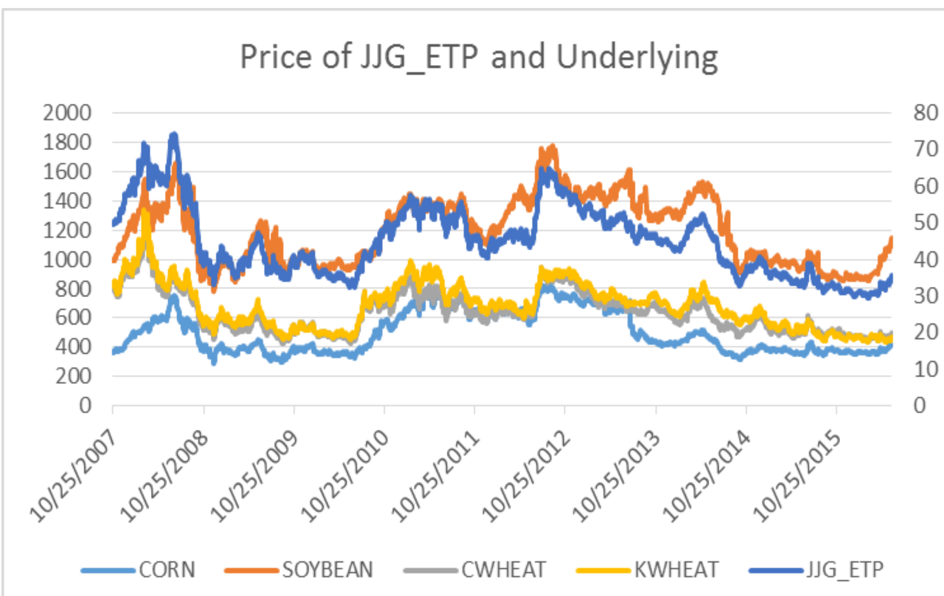
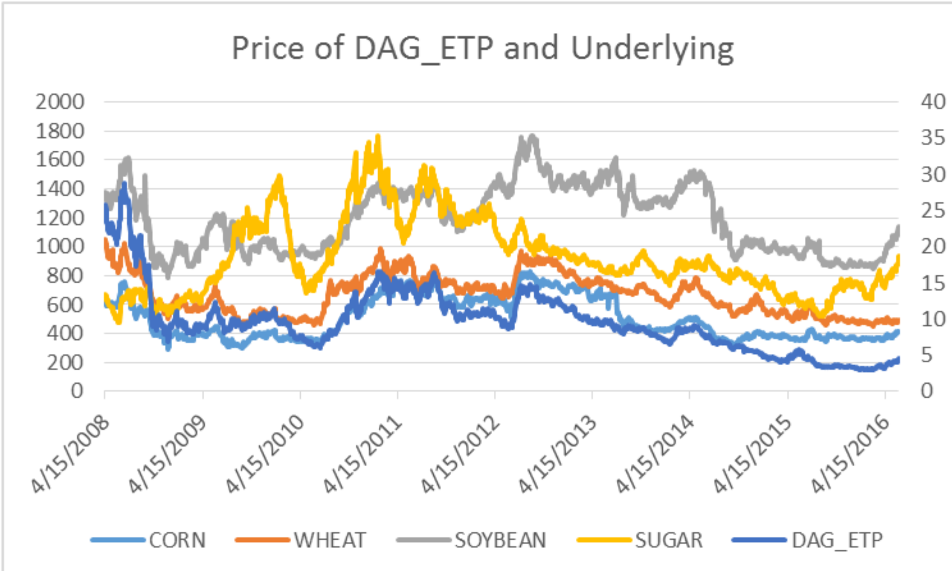


Figure 4.5: Historical price of DAG_ETP and underlying



Figures 4.1 – 4.5 show historical price data of ETPs along with commodity underlying. As we can see, the price of CORN_ETP, SOYB_ETP and WEAT_ETP along with underlying started low and suddenly peaked in the year of 2012, then followed by a gradual slump. The price of JJG_ETP and DAG_ETP along with commodity underlying started high in mid-2008 and ended low by 2016 after experiencing fluctuated years. This fluctuation of grain commodity market might result from several economic and non-economic issues, such as the 2007-2008 financial crisis and the 2012-2013 drought. In addition, roughly speaking, these graphs indicate the movement of ETPs go consistently with their underlying throughout the period.

Table 4.1: Summary Statistics

Table 4.1 presents summary statistics of five ETPs and their underlying components. C1, C2 and C3 represent the second-to-expire CBOT Corn Futures Contract, the third-to-expire CBOT Corn Futures Contract and the CBOT Corn Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Similarly, S1, S2 and S3 represent soybean futures contracts, and W1, W2 and W3 represent wheat futures contracts. The sample data are from different time ranges. Specifically, CORN and their underlying are in 06/08/2010-03/14/2016 WEAT and their underlying are in 09/19/2011-03/14/2016, SOYB and their underlying are in 09/19/2011-03/14/2016, JJG and their underlying are in 10/23/2007-03/14/2016, and DAG and their underlying are in 04/15/2008-03/14/2016. St. Dev stands for "standard deviation."

Table 4.1

Variables	Obs.	Mean	St.Dev.	Median	Min	Max	Skewness	Kurtosis
C1	1437	534.648	141.537	507.500	333.250	838.750	0.269	-1.378
C2	1437	531.832	133.265	506.750	342.000	837.750	0.371	-1.208
C3	1437	505.415	86.795	505.500	366.750	681.500	0.139	-1.308
CORN_ETP	1437	34.812	8.702	35.120	20.535	52.670	0.036	-1.247
W1	1117	634.321	117.184	638.000	446.000	948.250	0.635	-0.176
W2	1117	644.017	116.871	651.250	452.500	936.500	0.559	-0.275
W3	1117	667.587	106.502	680.000	477.500	910.000	0.198	-0.783
WEAT_ETP	1117	16.180	4.930	16.290	8.560	25.350	0.133	-1.295
S1	1121	1225.795	232.237	1272.000	855.250	1768.250	-0.040	-1.100
S2	1121	1207.092	217.536	1257.750	855.500	1766.250	0.043	-0.874
S3	1121	1136.369	160.109	1176.500	859.750	1552.500	-0.214	-1.130
SOYB_ETP	1121	22.259	2.690	22.830	17.060	28.850	-0.226	-0.755
CORN	2157	500.012	142.728	441.000	293.500	831.250	0.550	-1.152
SOYBEAN	2157	1195.262	225.623	1205.000	783.500	1771.000	0.190	-1.100
CWHEAT	2157	638.508	142.151	624.500	428.000	1280.000	0.843	0.564
KWHAET	2157	681.148	157.309	680.750	430.760	1337.000	0.519	-0.076
JJG_ETP	2157	45.025	9.652	44.620	29.480	74.430	0.528	-0.388
CORN	1914	502.758	145.353	438.250	293.500	831.250	0.523	-1.227
WHEAT	1914	666.240	138.043	676.000	453.500	1051.500	0.319	-0.925
SOYBEAN	1914	1194.027	228.851	1199.250	781.750	1771.000	0.192	-1.138
SUGAR	1914	18.599	5.361	17.320	9.530	35.310	0.734	-0.207
DAG_ETP	1914	9.514	4.369	9.175	2.940	28.780	1.112	2.329

In Table 4.1, observations of sample data are diverse, due to different inception dates. The big gap between minimum and maximum price of each security indicates the grain ETPs and commodity underlying have been through a volatile period. Speaking of the skewness, it is to measure the asymmetry of the probability distribution of a random variable. Most of estimates of skewness are moderate positive, within the range of -1 to 1, which means the bulk of the data lies to the right of the mean. This implies that the price of commodity is tending to rise up. Few variables, such as S1, S3 and SOYB_ETP, show negative skewness in price, which means that the majority of the data lies to the left of the mean, Furthermore, kurtosis is a measure of the 'peakedness' of the probability distribution of a random variable, which describes the shape of a probability distribution. Most estimates of kurtosis are slightly negative, which displays platykurtic shapes with an acute tails and a fatter peak around the mean for the sampled period. Since all the estimates are within the range from -3 to 3, they are all acceptable. Compared to kurtosis values of each underlying, DAG_ETP's and WEAT_ETP's are fairly higher, which indicates that the data tends to have light peak, or outliers.

4.2 Price Discovery between ETPs and Underlying

4.2.1 Stationarity Test

Two methods are implemented to test the existence of stationarity of the date: The Augmented Dickey-Fuller (ADF) test and the Phillip and Perron (PP) test. The ADF test is an augmented version of the Dickey–Fuller test for a more complex time series model, allowing autocorrelation at higher order lags. The null hypothesis of an ADF test is that there is a unit root present in a time series sample. The Phillips Perron test that builds on the Dickey–Fuller test of the null hypothesis is helpful to test the unit root in the data that has a high order of autocorrelation.

Table 2: Stationarity Test

Table 4.2 reports the results of unit root tests (Augmented Dickey-Fuller and Phillips-Perron). C1, C2 and C3 represent the second-to-expire CBOT Corn Futures Contract, the third-to-expire CBOT Corn Futures Contract and the CBOT Corn Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Similarly, S1, S2 and S3 represent soybean futures contracts, and W1, W2 and W3 represent wheat futures contracts.

Table 4.2

Security	ADF Test		PP Test		Decision
	Statistics	P Value	Alpha	P Value	
C1	-1.418	0.531	-12.190	0.429	Fail to Reject
C2	-1.454	0.517	-12.657	0.404	Fail to Reject
C3	-1.535	0.487	-13.312	0.367	Fail to Reject
CORN_ETP	-1.046	0.670	-10.124	0.545	Fail to Reject
S1	-0.847	-0.847	-7.504	0.691	Fail to Reject
S2	-0.961	0.744	-9.134	0.600	Fail to Reject
S3	-1.286	0.580	-18.684	0.091	Fail to Reject
SOYB_ETP	-1.580	0.470	-9.852	0.560	Fail to Reject
W1	-1.295	0.577	-10.583	0.519	Fail to Reject
W2	-1.226	0.602	-10.447	0.527	Fail to Reject
W3	-1.257	0.591	-12.521	0.411	Fail to Reject
WEAT_ETP	-1.182	-1.182	-15.234	0.260	Fail to Reject
CORN	-1.819	0.3807	-7.399	0.697	Fail to Reject
SOYBEAN	-2.444	0.1472	-10.169	0.5425	Fail to Reject
CWHEAT	-2.621	0.0915	-14.381	0.3076	Fail to Reject
KWHAET	-2.120	0.2684	-11.593	0.4631	Fail to Reject
JJG_ETP	-1.887	0.3554	-9.8221	0.5619	Fail to Reject
CORN	-1.862	0.3646	-6.754	0.733	Fail to Reject
WHEAT	-2.790	0.06332	-12.729	0.3998	Fail to Reject
SOYBEAN	-2.359	0.179	-8.7977	0.619	Fail to Reject
SUGAR	-2.071	0.2867	-8.9835	0.6087	Fail to Reject
DAG_ETP	-3.521	0.01	-18.016	0.1048	Fail to Reject

Table 4.2 presents two types of stationarity test: ADF test and PP test. All the tests show lack of statistical significance against the null hypothesis of unit root or non-

stationarity, so that fail to reject the null hypothesis. Thus, it concludes that the price data of securities are non-stationary. Next, the cointegration test is described below.

4.2.2 Cointegration Test

Johansen (1988) develops maximum likelihood estimators of cointegrating vectors and provides a rank test to determine the number of cointegrating vectors, r. In this study, the Johansen test has been used to investigate the cointegrated relationship between each ETP and commodity underlying, includes two types of tests maximal trace test and maximal eigenvalue test. In this study, we adopt maximal eigenvalue test as an indicator, testing the null hypothesis that there are (at most) r ($0 < r < p$) cointegrated vectors. To be accurate, this study proposes an assumption during the test: whether there is a linear trend existing in the model.

Table 4.3: Cointegration Test

Table 4.3 presents summary of cointegration test for each ETP and underlying. C1, C2 and C3 represent the second-to-expire CBOT Corn Futures Contract, the third-to-expire CBOT Corn Futures Contract and the CBOT Corn Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Similarly, S1, S2 and S3 represent soybean futures contracts, and W1, W2 and W3 represent wheat futures contracts. Cwheat and Kwheat represent nearby Chicago Wheat Futures Contract and Kansas Wheat Futures Contract respectively. All tests adopt maximal eigenvalue statistic under two types of methods: without/with linear trend. Within the result, 'r' means the number of cointegrated relationship, and 'test' means values of test statistic. All the tests reject the hypothesis, which imply the existence of cointegration.

Table 4.3

Securities	H_0=r	Without linear trend Test	5% Critical Value	With linear trend Test	5% Critical Value
C1	r=0	37.31	28.14	37.57	31.46
C2	r<=1	31.98	22.00	32.77	25.54
C3	r<=2	7.69	15.67	7.65	18.96
CORN_ETP	r<=3	3.62	9.24	4.50	12.25
S1	r=0	31.40	28.14	45.52	31.46
S2	r<=1	15.42	22.00	15.50	25.54
S3	r<=2	10.97	15.67	13.78	18.96
SOYB_ETP	r<=3	4.83	9.24	8.78	12.25
W1	r=0	37.52	28.14	37.99	31.46
W2	r<=1	15.58	22.00	18.70	25.54
W3	r<=2	10.37	15.67	12.06	18.96
WEAT_ETP	r<=3	4.76	9.24	4.75	12.25
CORN	r=0	43.16	34.40	44.89	37.52
SOYBEAN	r<=1	20.40	28.14	24.70	31.46
K.WHEAT	r<=2	15.87	22.00	16.86	25.54
C.WHEAT	r<=3	6.11	15.67	7.17	18.96
JJG_ETP	r<=4	3.77	9.24	4.15	12.25
CORN	r=0	541.55	34.40	523.09	37.52
SOYBEAN	r<=1	37.71	28.14	47.10	31.46
WHEAT	r<=2	20.72	22.00	27.69	25.54
SUGAR	r<=3	14.87	18.96	14.93	18.96
DAG_ETP	r<=4	4.54	9.24	6.14	12.25

Table 4.3 displays results of the cointegration test for each ETP and its underlying. Taking CORN_ETP and its underlying components for example. When the finding of the hypothesis of r<=0 and r<=1 is much larger than 5% critical value, it presents the hypothesis is rejected, which means there are at least two cointegration among CORN_ETP, C1,C2 and C3 (i.e., the intercepts in the long-run relations). Similarly, tests for WEAT_ETP and SOYB_ETP and their underlying have all been witnessed to reject the hypothesis of r<=0 at 5% critical value, resulting in the evidences of at least one cointegrated relationships among them respectively. Also, the test of JJG_ETP rejects the

hypothesis of r<=1 at 5% critical value, which shows at least two cointegrated relationship existing among JJG_ETP, corn futures, soybean futures, Kwheat futures and Cwheat futures. Besides, the test of DAG_ETP rejects the hypothesis of r<=0 and r<=1 at 5% critical value, which illustrates multiple cointegration existing between DAG_ETP, corn futures, soybean futures, wheat futures and sugar futures. Therefore, it concludes that failed rejections of the null hypothesis imply that there exists at least two co-integrating vector which confirms a long run equilibrium relationship between the each agricultural ETP and underlying.

4.2.3 Mean Equation (VEC model)

From the test of cointegration, it shows the evidence of cointegration between variables, which suggests a long term relationship between variables. To avoid the noise of cointegration, the VEC model is necessary to be applied. The VEC model allows the long run behavior of the endogenous variables to converge to their long run equilibrium relationship while allowing a wide range of short run dynamics.

Tables 4.4-4.8 report results of VEC models of five ETPs, CORN_ETP, WEAT_ETP, SOBY_ETP, JJG_ETP, DAG_ETP and their underlying. With regard to CORN_ETP, the long run equilibrium relationships from $CORN\_ETP_{t-1}$ to $\Delta C2_t$ and $\Delta C3_t$ are confirmed, which are statistically significant at 1% and 10% level respectively. Yet, there is no evidence of long run relationships from underlying to $\Delta CORN\_ETP_t$. This means the impact of the CORN_ ETP's price movement, in the long run, can be transmitted to its underlying, especially C1 and C2, and not vice versa. Furthermore, the short run price transmissions from $\Delta CORN\_ETP_{t-1}$ to $\Delta C1_t$, $\Delta C2_t$ and $\Delta C3_t$ are obtained, which shows 1%, 1% and 10% statistical significance level respectively, and not vice versa. This means impacts from the CORN_ETP is significant to the price movement of C1, C2 and C3 in the short run. Overall, there is a unilateral relationship from the CORN_ETP to C2 and C3 in the long run, while there are unilateral relationships from the CORN_ETP to its underlying in the short run, C1 and C2 in particularly.

With regard to SOYB_ETP, the long run equilibrium relationships from $SOYB\_ETP_{t-1}$ to $\Delta S1_{t,}$ $\Delta S2_t$ and $\Delta S3_t$ are confirmed, which are statistically significant at 1%, 1% and 5% level respectively. And, there also exists a long run relationship from $S1_{t-1}$ to $\Delta SOYB\_ETP_{t,}$ at 5% significance level. This means, in the long run, the impact of the SOYB_ ETP's price movement can be transmitted to all of its underlying, while the impact of S1 can be transmitted to SOYB_ ETP. Furthermore, the short run price transmissions from $\Delta S2_{t-1}$ and $\Delta S3_{t-1}$ to $\Delta SOYB\_ETP_t$ are observed, which shows 5% and 5% statistical significance level respectively, and not vice versa. This means impacts from the S2 and S3 are significant to the price movement of SOYB_ ETP in the short run. Overall, in the long run, there are unilateral relationships from the SOYB_ETP to S2 and S3 and a bilateral relationship between SOYB_ETP and S1, while there are unilateral relationships from S2 and S3 to SOYB_ETP in the short run.

With regard to WEAT_ETP, the long run equilibrium relationships from $WEAT\_ETP_{t-1}$ to$\Delta W1_t$ and $\Delta W3_t$ are confirmed, which are statistically significant at 5% and 5% level respectively. And, there also exist long run relationships from $W2_{t-1}$ and $W3_{t-1}$ to $\Delta WEAT\_ETP_{t,}$ at 10% and 5% significance level respectively. This means, in the long run, the impact of the WEAT_ETP's price movement can be transmitted to its underlying, such as W1 and W3, while the price impact of W2 and W3 can be transmitted to WEAT_

ETP. Furthermore, there is no evidence that shows a unilateral or bilateral relationship between the WEAT_ETP and its underlying in the short run, since none of their coefficients is statistically significant. Overall, there, in the long run, are a unilateral relationship from the WEAT_ETP to W1 and a unilateral relationship from W2 to WEAT_ETP, as well as a bilateral relationship between WEAT_ETP and W3, while there is no evidence of equilibrium relationships between WEAT_ETP and the underlying in the short run.

Regarding to the JJG_ETP, the long run equilibrium relationships from JJG_ETP_{t-1} to $\Delta CORN_t$ and $\Delta KWHEAT_t$ are confirmed, which are statistically significant at 1% and 5% level respectively, while there is no relationship observed from underlying to the JJG_ETP. This means, in the long run, the impact of the JJG_ETP's price movement can be transmitted to its underlying, such as CORN and KWHEAT, and not vice versa. Furthermore, the short run price transmission from ΔJJG_ETP_{t-1} to $\Delta SOYBEAN_{t,}$ $\Delta CWHEAT_t$ and $\Delta KWHEAT_t$ are observed, which shows 1%, 10% and 1% statistical significance level respectively, and not vice versa. Overall, in the long run, there are unilateral relationships from JJG_ETP to corn futures and Kansas wheat futures, while there are strong unilateral relationships from JJG_ETP to soybean futures and Kansas wheat futures in the short run.

In regards to DAG_ETP, the long run equilibrium relationships from DAG_ETP_{t-1} to $\Delta SOYBEAN_t$, $\Delta WHEAT_t$, and $\Delta SUGAR_t$ are confirmed, which are statistically significant at 10%, 10% and 10% level respectively, while only a long relationship from $CORN_{t-1}$ to ΔDAG_ETP_t is observed too at 1% significance level. This means, in the long run, the impact of the CORN's price movement can be transmitted to DAG_ETP, while DAG_ETP has a slight impact on its underlying, such as SOYBEAN, WHEAT and

SUGAR. Furthermore, the short run price transmission from $\Delta CORN_{t-1}$, $\Delta WHEAT_{t-1}$ and $\Delta SUGAR_{t-1}$ to ΔDAG_ETP_t are observed, which shows 5%, 5% and 10% statistical significance level respectively, and not vice versa. Overall, there is, in the long run, a unilateral relationship from corn futures to DAG_ETP, while there are unilateral relationships from corn futures and wheat futures to DAG_ETP in the short run.

Table 4.4: VEC Model's results of CORN_ETP and underlying

Table 4.4 presents the output of VEC model about the CORN_ETP and its underlying. C1, C2 and C3 represent the second-to-expire CBOT Corn Futures Contract, the third-to-expire CBOT Corn Futures Contract and the CBOT Corn Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Values without parentheses are estimated parameters, values below parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.4

	$\Delta CORN\_ETP_t$	$\Delta C1_t$	$\Delta C2_t$	$\Delta C3_t$
$CORN\_ETP_{t-1}$	0.005	0.166	0.530	0.265
	0.646	0.41	0.00 ***	0.06*
$C1_{t-1}$	0.000	-0.034	-1.326	0.008
	0.880	0.016**	0.174	0.407
$C2_{t-1}$	0.001	0.039	-1.027	0.005
	0.503	0.005***	0.00 ***	0.616
$C3_{t-1}$	-0.002	-0.035	-0.461	-0.058
	0.067*	0.110	0.00 ***	0.00 ***
$\Delta CORN\_ETP_{t-1}$	-0.085	5.784	3.751	1.722
	0.237	0.00 ***	0.001***	0.062*
$\Delta C1_{t-1}$	-0.001	-0.149	-0.105	-0.070
	0.891	0.021**	0.100	0.135
$\Delta C2_{t-1}$	-0.004	0.027	0.024	0.014
	0.234	0.686	0.71	0.773
$\Delta C3_{t-1}$	-0.004	-0.274	-0.212	-0.121
	0.324	0.001***	0.014**	0.05*

Table 4.5: VEC Model's results of SOYB_ETP and underlying

Table 4.5 presents the output of VEC model about the SOYB_ETP and its underlying.
S1, S2 and S3 represent the second-to-expire CBOT Soybean Futures Contract, the third-to-expire CBOT Soybean Futures Contract and the CBOT Soybean Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Values without parentheses are estimated parameters, values below parameter estimates are p-values. ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.5

	ΔSOYB_ETP$_t$	$\Delta S1_t$	$\Delta S2_t$	$\Delta S3_t$
SOYB_ETP$_{t-1}$	-0.050	-1.747	-1.736	-1.692
	0.00 ***	0.033**	0.030**	0.001***
$S1_{t-1}$	0.001	-0.015	0.013	0.057
	0.023*	0.522	0.560	0.002
$S2_{t-1}$	-0.002	0.029	-0.001	-0.024
	0.443	0.164	0.970	0.149
$S3_{t-1}$	0.000	0.008	0.001	-0.045
	0.644	0.628	0.935	0.00***
ΔSOYB_ETP$_{t-1}$	-0.458	-2.058	-1.192	-0.010
	0.00 ***	0.475	0.672	0.775
$\Delta S1_{t-1}$	0.001	0.061	-0.012	-0.036
	0.367	0.518	0.896	0.636
$\Delta S2_{t-1}$	0.003	-0.014	-0.033	-0.016
	0.043**	0.888	0.739	0.840
$\Delta S3_{t-1}$	0.002	-0.044	-0.025	-0.003
	0.036**	0.464	0.669	0.946

Table 4.6: VEC Model's results of WEAT_ETP and underlying

Table 4.6 presents the output of VEC model about the WEAT_ETP and its underlying. W1, W2 and W3 represent the second-to-expire CBOT Wheat Futures Contract, the third-to-expire CBOT Wheat Futures Contract and the CBOT Wheat Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Values without parentheses are estimated parameters, values below parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.6

	$\Delta WEAT\_ETP_t$	$\Delta W1_t$	$\Delta W2_t$	$\Delta W3_t$
$WEAT\_ETP_{t-1}$	-0.057	-1.532	-1.818	-1.246
	0.00 ***	0.014**	0.386	0.026**
$W1_{t-1}$	-0.002	-0.141	-0.073	-0.073
	0.229	0.089*	0.356	0.323
$W2_{t-1}$	0.005	0.214	0.136	0.148
	0.062*	0.036**	0.165	0.105
$W3_{t-1}$	-0.002	-0.062	0.053	-0.070
	0.014**	0.017**	0.033**	0.002***
$\Delta WEAT\_ETP_{t-1}$	-0.464	-2.107	-1.818	-0.715
	0.00 ***	0.337	0.386	0.715
$\Delta W1_{t-1}$	0.008	0.309	0.334	0.125
	0.142	0.173	0.123	0.535
$\Delta W2_{t-1}$	0.004	-0.195	-0.249	-0.060
	0.609	0.496	0.364	0.814
$\Delta W3_{t-1}$	-0.001	-0.103	-0.072	-0.097
	0.751	0.309	0.459	0.282

Table 4.7: VEC Model's results of JJG_ETP and underlying

Table 4.7 presents the output of VEC model about the JJG_ETP and its underlying. CORN represent the nearby CBOT Corn Futures Contract. Similarly, SOYBEAN, CWHEAT represent the nearby CBOT Soybean Futures Contract. KWHEAT represent nearby Kansas Wheat Futures Contract. Values without parentheses are estimated parameters, values below parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.7

	ΔJJG_ETP_t	$\Delta CORN_t$	$\Delta SOYBEAN_t$	$\Delta CWHEAT_t$	$\Delta KWHEAT_t$
JJG_ETP_{t-1}	-0.023	-0.321	-0.029	0.013	0.331
	0.018**	0.009***	0.913	0.944	0.003**
$CORN_{t-1}$	0.000	-0.002	0.014	-0.001	-0.079
	0.535	0.503	0.034*	0.859	0.157
$SOYBEAN_{t-1}$	0.000	0.002	-0.017	0.004	-0.128
	0.448	0.459	0.006***	0.315	0.015*
$CWHEAT_{t-1}$	0.001	0.012	0.013	-0.009	-0.175
	0.129	0.165	0.488	0.504	0.048 *
$KWHEAT_{t-1}$	0.000	0.005	-0.001	-0.003	-0.939
	0.774	0.493	0.934	0.916	0.001 **
ΔJJG_ETP_{t-1}	-0.012	0.042	6.967	2.144	2.747
	0.125	0.955	0.00 ***	0.053*	0.00***
$\Delta CORN_{t-1}$	-0.001	0.034	-0.256	-0.134	-0.158
	0.726	0.338	0.00 ***	0.012**	0.002***
$\Delta SOYBEAN_{t-1}$	0.002	0.049	-0.112	-0.012	-0.055
	0.115	0.001***	0.00 ***	0.543	0.117
$\Delta CWHEAT_{t-1}$	-0.006	-0.082	-0.160	-0.181	-0.147
	0.079*	0.085*	0.245	0.043**	0.007***
$\Delta KWHEAT_{t-1}$	0.004	0.039	0.039	0.136	0.180
	0.125	0.413	0.703	0.055*	0.007***

Table 4.8: VEC Model's results of DAG_ETP and underlying

Table 4.8 presents the output of VEC model about the DAG_ETP and its underlying. CORN represent the nearby CBOT Corn Futures Contract. Similarly, SOYBEAN, CWHEAT represent the nearby CBOT Soybean Futures Contract. KWHEAT represent nearby Kansas Wheat Futures Contract. Values without parentheses are estimated parameters, values below parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.8

	ΔDAG_ETP_t	$\Delta CORN_t$	$\Delta SOYBEAN_t$	$\Delta WHEAT_t$	$\Delta SUGAR_t$
DAG_ETP_{t-1}	-0.225	-0.281	0.612	-0.340	-0.014
	0.00 ***	0.115	0.083*	0.073*	0.053*
$CORN_{t-1}$	0.000	-0.010	0.012	0.009	0.000
	0.004**	0.528	0.226	0.092*	0.923
$SOYBEAN_{t-1}$	0.000	-0.003	-0.018	0.004	0.000
	0.988	0.902	0.00***	0.145	0.607
$WHEAT_{t-1}$	0.000	0.015	0.025	-0.016	0.000
	0.284	0.191	0.025**	0.027**	0.573
$SUGAR_{t-1}$	0.003	0.149	0.059	0.091	-0.005
	0.051'	0.178	0.633	0.199	0.066*
ΔDAG_ETP_{t-1}	-0.074	0.135	1.252	0.097	0.016
	0.069*	0.923	0.648	0.951	0.797
$\Delta CORN_{t-1}$	0.002	0.031	0.060	-0.007	0.003
	0.034**	0.346	0.356	0.849	0.040**
$\Delta SOYBEAN_{t-1}$	0.000	0.020	-0.098	0.015	0.001
	0.303	0.159	0.00***	0.364	0.417
$\Delta WHEAT_{t-1}$	-0.002	-0.056	-0.013	-0.059	-0.002
	0.032**	0.057*	0.829	0.078*	0.122
$\Delta SUGAR_{t-1}$	0.035	1.229	1.995	2.264	-0.046
	0.071*	0.061*	0.125	0.002***	0.078*

4.3 Information Share of ETPs and Underlying

A market's contribution to price discovery is the "information share". According to Hasbrouck (1995), information share measures the market's contribution to which is the proportion of the efficient price innovation variance that can be attributed to that market. This efficient price is unobservable, but common to all the markets. Intuitively, information share proxies for 'who moves first' in the price discovery.

Table 4.9 reports information share is allocated differently in ETPs and underlying components. Taking CORN_ETP and its underlying for example. The information share of C1 counts much more than C2, C3 and CORN_ETP, about 0.803, while that of

CORN_ETP is lowest, about 0.028. This means C1 is most likely to move first when new innovation comes and CORN_ETP will reflect it at last. Similarly, the information share of S1 and W1 take the dominant proportions, about 0.817 and 0.898 respectively, while that of SOYB_ETP and WEAT_ETP are the lowest, about 0.038 and 0.032 respectively. This means S1 and W1 will probably first reflect new innovation compared to other related securities. As with JJG_ETP, the finding shows that the information share of CORN, SOYBEAN and CWHEAT dominant, which are about 0.508, 0.176 and 0.254 respectively, while that of JJG_ETP is the lowest. This implies that JJG_ETP's underlying are most likely to move faster than JJG_ETP in response to new information while JJG_ETP moves at last. Similarly, it applies to DAG_ETP. The information of CORN, SOYBEAN and WHEAT counts more than others, about 0.261, 0.146 and 0.308 respectively, while that of DAG_ETP is the lowest, about 0.036.

To summarize, the findings imply that the information share of ETPs' underlying are much higher than ETPs, which means the price of underlying commodities moves faster than ETPs when new information comes. Interestingly, in three single commodity based ETPs, all the nearby futures contracts have the largest information share. That demonstrates that they are more informative to new shocks in the futures market.

Table 4.9: Estimates of information share of ETPs and underlying components

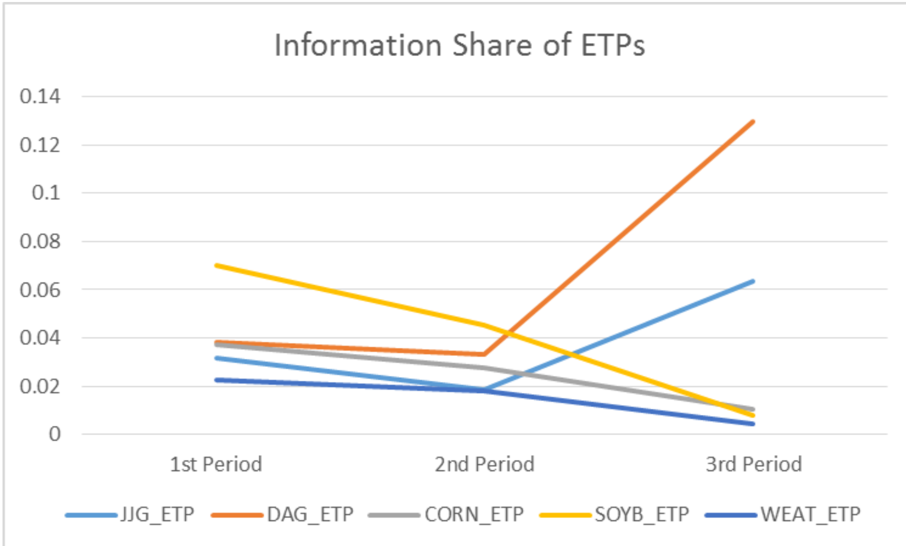
Table 4.9 reports the estimate of information share for each ETP and its underlying. Larger value means more contribution which indicates that particular market reflects faster when new information comes.

Table 4.9

Information Share			
C1	0.803	CORN	0.508
C2	0.089	SOYBEAN	0.176
C3	0.077	CWHAT	0.254
CORN_ETP	0.028	KWHEAT	0.033
		JJG_ETP	0.027
S1	0.817		
S2	0.026	CORN	0.261
S3	0.116	SOYBEAN	0.146
SOYB_ETP	0.038	WHEAT	0.308
		SUGAR	0.145
W1	0.898	DAG_ETP	0.036
W2	0.046		
W3	0.022		
WEAT_ETP	0.032		

Due to kinds of economic and non-economic events, information share of each security is changing throughout the time. It might be affected by trading volume and spread, security volatility and important financial regulations. In the Figure 4.6 as below, it presents the magnitude of information share of each ETP throughout the history, which are divided by three periods. As we can see, CORN_ETP, SOYB_ETP and WEAT_ETP have a decreasing information share trend throughout the whole period while the information share of JJG_ETP and DAG_ETP slumps in the beginning, followed by a sharp jump.

Figure 4.6: Information share of ETPs throughout the history



4.4 Volatility Spillover between ETPs and Underlying

In the BEKK model, the diagonal elements in matrix A capture the ARCH effect, and the off-diagonal elements of matrix A capture the cross-market shock spillover, whereas the diagonal elements in matrix B measure the GARCH effect, and the off-diagonal elements of matrix B capture the cross-market volatility spillover.

As shown in Table 4.10, the diagonal elements of α_{11}, α_{22}, α_{33} and α_{44} show strong statistical significance. This presents the existence of ARCH effects among CORN_ETP and underlying components themselves. In particularly, the statistical significance of α_{44} illustrates that the volatility of CORN_ETP is directly affected by its own shocks to return. Looking at the coefficients of α_{14} and α_{34}, all presents strong statistical significance at 1% significance level. This means shocks of returns from C1 and C3 have crucial influence on the volatility of CORN_ETP. Meanwhile, the fact that α_{41}, α_{42} and α_{43} have statistical significance at 1% level indicates strong volatility linkages/transmission from CORN_ETP to C1, C2 and C3 respectively. Thus, it concludes that there exist bi-directional shock transmissions between the CORN_ETP and the underlying of C1 and C3, and a unidirectional shock transmission from CORN_ETP to C2.

In addition, the diagonal elements of β_{11} , β_{22} , β_{33} and β_{44} depict strong statistical significance. This presents the existence of GARCH effects for each security itself. The significance of β_{44} , in particularly, illustrates that volatility of the CORN_ETP is directly affected by its own past volatility. The coefficients β_{14} , β_{24} and β_{34} are statistically significant at the 1% level. This implies strong volatility spillover effects from the underlying futures C1, C2, and C3 to CORN_ETP. In other words, when the past volatility of C1 rises up for a certain reason, it is highly possible to affect the volatility of CORN_ETP. So as C2 and C3 to CORN_ETP. Meanwhile, the coefficients of β_{41} , β_{42} and β_{43} are statistically significant at the 1% level. This shows that there are strong volatility transmission effects from CORN_ETP to C1, C2 and C3. Thus, the above findings imply the evidence of bi-directional volatility spillover effects between the CORN_ETP and its underlying of C1, C2 and C3.

Due to a great success of the issuing of CORN_ETP, Teucrium continued to introduce additional ETPs: SOYB_ETP and WEAT_ETP. As shown in Table 4.11, the diagonal elements of α_{11} , α_{22} , α_{33} and α_{44} show strong statistical significance. This presents the existence of ARCH effects among the SOYB_ETP and underlying themselves. In particularly, the significance of α_{44} illustrates that volatility of the SOYB_ETP is directly affected by its own shock to price. Considering the coefficient of α_{14} , it displays strong statistical significance at 1% significance level. This means shocks from S1 has significant influence on the volatility of SOYB_ETP. In addition, the fact that coefficients of α_{41} and α_{42} show statistical significance at 1% level, indicates strong shocks linkages/transmissions from SOYB_ETP to S1 and S2. Thus, it concludes that there exist a bi-directional shock transmission between the SOYB_ETP and S1, and a unidirectional shocks linkages from SOYB_ETP to S2.

In addition, the diagonal elements of β_{11} , β_{22} , β_{33} and β_{44} have strong statistical significance, which presents the existence of GARCH effects for SOYB_ETP and underlying themselves. The significance of β_{44} , in particularly, illustrates that volatility of the SOYB_ETP is directly affected by its own past volatility. The coefficients of β_{14} and β_{34} are statistically significant at 1% level. This implies strong volatility spillover effects from S1and S3 to the SOYB_ETP. In other words, when the past volatility of S1 or S3 rises up for certain reason, it is highly possible to affect the volatility of SOYB_ETP. Meanwhile, none of β_{41} β_{42} and β_{43} are statistically significant, which shows that there are not strong volatility transmission effects from SOYB to S1, S2 and S3. Thus, the above findings imply the evidence of unidirectional volatility spillover effects from S1 and S3 to SOYB_ETP.

As shown in Table 4.12, the diagonal elements of α_{11}, α_{22}, α_{33} and α_{44} show strong statistical significance at 1% level. This presents the existence of ARCH effects for WEAT_ETP and underlying themselves. In particularly, the significance of α_{44} implies that volatility of the WEAT_ETP is directly affected by its own shock to price. Looking at the coefficients of α_{14} α_{24} and α_{34}, they display strong statistical significance at 1% significance level. This means shocks from W1, W2 and W3 exert crucial influence on the volatility of WEAT_ETP. Also, the fact that α_{42} and α_{43} have statistical significance at 1% significance level, indicates strong volatility linkages/transmissions from WEAT_ETP to W2 and W3.Thus, the findings imply the evidence of bi-directional shock transmission linkages between the WEAT_ETP and its underlying of W2, W3, and a unidirectional shock transmission linkage from W1 to WEAT_ETP.

In addition, the diagonal elements of β_{11}, β_{22}, β_{33} and β_{44} show strong statistical significance. This presents the existence of GARCH effects for WEAT_ETP and underlying themselves. The significance of β_{44}, in particularly, illustrates that the volatility of the WEAT_ETP is directly affected by its own past volatility. The coefficients of β_{14}, β_{24} and β_{34} are statistically significant at 1% level. This implies strong volatility spillover effects from W1, W2 and W3 to the WEAT_ETP. In other words, when the past volatility of W1 rises up for certain reasons, it is highly possible to affect the volatility of WEAT_ETP. So as W2 andW3 to WEAT_ETP. Also, the coefficients of β_{43} is statistically significant at 1% level. This shows that there is strong volatility transmission effects from WEAT_ETP to W3. Thus, the above findings imply the evidence of bi-directional volatility spillover between the WEAT_ETP and W3 and unilateral volatility spillover from W1 and W2 to WEAT_ETP.

Regarding to JJG_ETP and DAG_ETP, results display similar views of volatility spillover effects between ETPs and underlying components. As shown in Table 4.13, the diagonal elements of α_{11} , α_{22} , α_{33} , α_{44} and α_{55} show strong statistical significance at 1% level. This presents the existence of ARCH effects for JJG_ETP and underlying themselves. In particularly, the significance of α_{55} illustrates that volatility of the JJG_ETP is directly affected by its own shock to price. The coefficients of α_{15} , α_{25} , α_{35} and α_{45} are statistically significant at 1% significance level. This means shocks from CORN, SOYB, CWHEAT and KWHEAT have crucial influence on the volatility of JJG_ETP. Also, α_{51} and α_{52} are statistically significant at 1% significance level. This implies strong volatility linkages/transmissions from JJG_ETP to CORN and SOYBEAN respectively. Besides the coefficients of α_{53} and α_{54} do not show statistical significance, which indicates no existence of volatility linkages from JJG_ETP to CWHAET and KWHEAT. Thus, the above findings imply evidences of bi-directional shock transmissions between the JJG_ETP and corn futures and soybean futures, and unidirectional shock transmissions from Chicago wheat futures and Kansas wheat futures to JJG_ETP.

In addition, the diagonal elements of β_{11} , β_{22} , β_{33} , β_{44} and β_{55} show strong statistical significance. This presents the existence of GARCH effects for JJG_ETP and underlying components themselves. The significance of β_{55}, in particularly, illustrates that volatility of the JJG_ETP is directly affected by its own past volatility. The coefficients of β_{15} and β_{25} are statistically significant at 1% level. This implies strong volatility spillover effects from CORN and SOYBEAN to JJG_ETP. In other words, when the past volatility of CORN or SOYBEARN rises up for certain reasons, it is highly possible to affect the volatility of JJG_ETP. Meanwhile, the coefficients of β_{51} and β_{52} are statistically significant at 1% level. This implies that there are strong volatility transmissions from JJG_ETP to the CORN and SOYBEAN. Thus, it concludes that there are bidirectional volatility spillover effects existing between JJG_ETP and corn futures and soybean futures.

As shown in Table 4.14, the diagonal elements of α_{11} , α_{22} , α_{33} , α_{44} and α_{55} show strong statistical significance at 1% or 5% level, which presents the existence of ARCH effects for DAG_ETP and underlying themselves. In particularly, the significance of α_{55} illustrates that the volatility of the DAG_ETP is directly affected by its own shock to price. The coefficients of α_{25} and α_{45} are statistically significant at 1% significance level. This means shocks from WHEAT and SUAGR have crucial influence on the volatility of DAG_ETP. Also, α_{51} , α_{52} , α_{53} and α_{54} are statistically significant at 1% or 5% level, which implies strong volatility linkages/transmissions from DAG_ETP to CORN, WHEAT, SOYBEAN and SUGAR. Thus, it concludes that there exists bi-directional shock transmissions between the DAG_ETP and wheat futures as well as sugar futures, and unidirectional shock transmissions from DAG_ETP to corn futures as well as soybean futures.

In addition, the diagonal elements of β_{11} , β_{22} , β_{33} , β_{44} and β_{55} show strong statistical significance at 1% level, which presents the existence of GARCH effects for DAG_ETP and underlying themselves. The significance of β_{55} , in particularly, illustrates that volatility of the DAG_ETP is directly affected by its own past volatility. The coefficients of β_{15} , β_{25} and β_{45} are statistically significant at 1% or 5% level. This implies volatility spillover effects from the past volatility of CORN, WHEAT and SUGAR to DAG_ETP. In other words, when the past volatility of CORN, WHEAT or SUGAR rises up for certain reasons, for example, it is highly possible to affect the volatility of DAG_ETP. So as wheat futures and sugar future to DAG_ETP. Also, the coefficients of β_{51} , β_{53} and β_{54} are statistically significant at 1% or 5% significance level, which shows there is a strong volatility transmission effect from DAG_ETP to the CORN, SOYBEAN and SUGAR. Thus, it concludes that there are bi-directional volatility spillover effects existing between the DAG_ETP and corn futures as well as sugar futures, and unilateral volatility spillovers from DAG_ETP to soybean futures and from wheat futures to DAG_ETP.

Table 4.10: BEKK Model's results of CORN_ETP and underlying

Table 4.10 reports the BEKK model output of the CORN_ETP and its underlying. C1, C2 and C3 represent the second-to-expire CBOT Corn Futures Contract, the third-to-expire CBOT Corn Futures Contract and the CBOT Corn Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Values without parentheses are estimated parameters, values in parentheses near parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.10

C1, C2, C3, CORN_ETP					
	Coefficient	P value		Coefficient	P value
α_{11}	0.680	(0.00)***	β_{11}	0.948	(0.00)***
α_{12}	-0.648	(0.00)***	β_{12}	0.210	(0.00)***
α_{13}	-0.115	(0.00)***	β_{13}	0.067	(0.00)***
α_{14}	-0.002	(0.00)***	β_{14}	0.011	(0.00)***
α_{21}	-0.749	(0.00)***	β_{21}	0.158	(0.00)***
α_{22}	1.046	(0.00)***	β_{22}	0.739	(0.00)***
α_{23}	0.104	(0.00)***	β_{23}	0.003	(0.22)
α_{24}	0.000	(0.25)	β_{24}	0.008	(0.00)***
α_{31}	-0.703	(0.00)***	β_{31}	0.175	(0.00)***
α_{32}	-1.254	(0.00)***	β_{32}	0.217	(0.00)***
α_{33}	-0.078	(0.00)***	β_{33}	0.832	(0.00)***
α_{34}	-0.013	(0.00)***	β_{34}	-0.011	(0.00)***
α_{41}	10.949	(0.00)***	β_{41}	-4.549	(0.00)***
α_{42}	11.783	(0.00)***	β_{42}	-2.592	(0.00)***
α_{43}	-0.310	(0.01)**	β_{43}	0.950	(0.00)***
α_{44}	0.107	(0.00)***	β_{44}	0.793	(0.00)***

Table 4.11: BEKK Model's results of SOYB_ETP and underlying

Table 4.11 reports the BEKK model output of the SOYB_ETP and its underlying, S1, S2 and S3 represent the second-to-expire CBOT Soybean Futures Contract, the third-to-expire CBOT Soybean Futures Contract and the CBOT Soybean Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Values without parentheses are estimated parameters, values in parentheses near parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.11

S1, S2, S3, SOYB_ETP					
	Coefficient	P value		Coefficient	P value
α_{11}	0.454	(0.00)***	β_{11}	1.164	(0.00)***
α_{12}	0.512	(0.00)***	β_{12}	0.198	(0.01)**
α_{13}	-0.467	(0.00)***	β_{13}	0.006	(0.65)
α_{14}	-0.004	(0.00)***	β_{14}	0.001	(0.00)***
α_{21}	-0.006	(0.81)	β_{21}	-0.272	(0.00)***
α_{22}	-0.141	(0.00)***	β_{22}	0.754	(0.00)***
α_{23}	0.343	(0.00)***	β_{23}	0.077	(0.00)***
α_{24}	0.001	(0.12)	β_{24}	-0.004	(0.26)
α_{31}	-0.047	(0.00)***	β_{31}	-0.146	(0.00)***
α_{32}	0.026	(0.02)**	β_{32}	-0.199	(0.00)***
α_{33}	0.562	(0.00)***	β_{33}	0.708	(0.00)***
α_{34}	0.000	(0.98)	β_{34}	-0.003	(0.00)***
α_{41}	-3.249	(0.00)***	β_{41}	0.215	(0.78)
α_{42}	-2.819	(0.01)**	β_{42}	-0.326	(0.67)
α_{43}	-1.870	(0.10)	β_{43}	-0.449	(0.51)
α_{44}	0.517	(0.00)***	β_{44}	0.853	(0.00)***

Table 4.12: BEKK Model's results of WEAT_ETP and underlying

Table 4.12 reports the BEKK model output of the WEAT_ETP and its underlying, W1, W2 and W3 represent the second-to-expire CBOT Wheat Futures Contract, the third-to-expire CBOT Wheat Futures Contract and the CBOT Wheat Futures Contract expiring in the December following the expiration month of the third-to-expire contract. Values without parentheses are estimated parameters, values in parentheses near parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.12

W1, W2, W3, WEAT_ETP					
	Coefficient	P value		Coefficient	P value
α_{11}	0.526	(0.00)***	β_{11}	0.809	(0.00)***
α_{12}	-0.114	(0.00)***	β_{12}	0.065	(0.00)***
α_{13}	0.121	(0.00)***	β_{13}	0.036	(0.00)***
α_{14}	0.000	(0.57)	β_{14}	0.004	(0.00)***
α_{21}	-0.199	(0.00)***	β_{21}	0.154	(0.00)***
α_{22}	0.591	(0.00)***	β_{22}	0.828	(0.00)***
α_{23}	0.289	0.00)***	β_{23}	-0.140	(0.00)***
α_{24}	0.003	(0.00)***	β_{24}	-0.006	(0.00)***
α_{31}	-0.074	(0.00)***	β_{31}	-0.027	(0.00)***
α_{32}	-0.210	(0.00)***	β_{32}	0.017	(0.00)***
α_{33}	-0.125	(0.00)***	β_{33}	0.997	(0.00)***
α_{34}	-0.004	(0.00)***	β_{34}	0.000	(0.04)**
α_{41}	0.381	(0.17)	β_{41}	0.020	(0.94)
α_{42}	-0.046	(0.84)	β_{42}	0.331	(0.29)
α_{43}	-2.440	(0.00)***	β_{43}	1.288	(0.01)**
α_{44}	0.249	(0.00)***	β_{44}	0.969	(0.00)***

Table 4.13: BEKK Model's results of JJG_ETP and Underlying

Table 4.13 reports the BEKK model output of the JJG_ETP and its underlying. CORN represent the nearby CBOT Corn Futures Contract. Similarly, SOYBEAN, CWHEAT represent the nearby CBOT Soybean Futures Contract. KWHEAT represent nearby Kansas Wheat Futures Contract. Values without parentheses are estimated parameters, values in parentheses near parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.13

CORN SOYBEAN CWHEAT KWHEAT JJG_ETP					
	Coefficient	P value		Coefficient	P value
α_{11}	0.240	(0.00)***	β_{11}	0.966	(0.00)***
α_{12}	0.136	(0.00)***	β_{12}	-0.036	(0.00)***
α_{13}	-0.100	(0.00)***	β_{13}	0.026	(0.00)***
α_{14}	-0.057	(0.01)**	β_{14}	0.015	(0.00)***
α_{15}	0.002	(0.04)**	β_{15}	-0.001	(0.00)***
α_{21}	0.037	(0.00)***	β_{21}	-0.010	(0.00)***
α_{22}	0.563	(0.00)***	β_{22}	0.870	(0.00)***
α_{23}	0.009	(0.27)	β_{23}	-0.003	(0.22)
α_{24}	0.020	(0.01)**	β_{24}	-0.005	(0.03)**
α_{25}	0.003	(0.00)***	β_{25}	0.000	(0.00)***
α_{31}	0.059	(0.01)**	β_{31}	-0.004	(0.15)
α_{32}	0.262	(0.00)***	β_{32}	-0.022	(0.11)
α_{33}	0.225	(0.00)***	β_{33}	0.967	(0.00)***
α_{34}	0.035	(0.00)***	β_{34}	-0.007	(0.23)
α_{35}	0.006	(0.00)***	β_{35}	0.000	(0.27)
α_{41}	-0.017	(0.06)*	β_{41}	0.003	(0.28)
α_{42}	-0.132	(0.00)***	β_{42}	0.022	(0.13)
α_{43}	0.069	(0.00)***	β_{43}	-0.010	(0.04)**
α_{44}	0.248	(0.00)***	β_{44}	0.970	(0.00)***
α_{45}	-0.003	(0.00)***	β_{45}	0.000	(0.13)
α_{51}	-2.324	(0.00)***	β_{51}	0.455	(0.00)***
α_{52}	-9.780	(0.00)***	β_{52}	2.276	(0.00)***
α_{53}	-0.071	(0.88)	β_{53}	-0.112	(0.25)
α_{54}	-0.701	(0.14)	β_{54}	0.014	(0.88)
α_{55}	0.034	(0.00)***	β_{55}	1.000	(0.00)***

Table 4.14: BEKK Model's results of DAG_ETP and Underlying

Table 4.14 reports the BEKK model output of the DAG_ETP and its underlying. CORN represent the nearby CBOT Corn Futures Contract. Similarly, SOYBEAN, WHEAT and SUGAR represent the nearby CBOT Soybean, Wheat and Sugar Futures Contract. Values without parentheses are estimated parameters, values in parentheses near parameter estimates are p-values. Note, ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Table 4.14

CORN WHEAT SOYBEAN SUGAR DAG_ETP					
	Coefficient	P value		Coefficient	P value
α_{11}	0.230	(0.00)***	β_{11}	0.962	(0.00)***
α_{12}	-0.063	(0.00)***	β_{12}	0.011	(0.10)
α_{13}	-0.275	(0.00)***	β_{13}	0.248	(0.00)***
α_{14}	0.000	(0.14)	β_{14}	0.000	(0.00)***
α_{15}	0.000	(0.14)	β_{15}	0.000	(0.02)**
α_{21}	0.042	(0.00)***	β_{21}	-0.014	(0.00)***
α_{22}	0.241	(0.00)***	β_{22}	0.955	(0.00)***
α_{23}	-0.029	(0.45)	β_{23}	-0.028	(0.33)
α_{24}	0.000	(0.21)	β_{24}	0.000	(0.00)***
α_{25}	0.000	(0.00)***	β_{25}	0.000	(0.02)**
α_{31}	-0.027	(0.00)***	β_{31}	0.016	(0.01)**
α_{32}	-0.004	(0.69)	β_{32}	0.005	(0.47)
α_{33}	0.601	(0.00)***	β_{33}	0.648	(0.00)***
α_{34}	-0.001	(0.00)***	β_{34}	0.000	(0.00)***
α_{35}	0.000	(0.54)	β_{35}	0.000	(0.05)*
α_{41}	1.410	(0.00)***	β_{41}	-0.215	(0.00)***
α_{42}	1.801	(0.00)***	β_{42}	-0.235	(0.00)***
α_{43}	6.016	(0.00)***	β_{43}	-1.253	(0.00)***
α_{44}	0.128	(0.00)***	β_{44}	0.990	(0.00)***
α_{45}	0.027	(0.00)***	β_{45}	-0.002	(0.00)***
α_{51}	1.294	(0.03)**	β_{51}	-0.369	(0.01)**
α_{52}	3.426	(0.00)***	β_{52}	-0.777	(0.10)
α_{53}	-17.573	(0.00)***	β_{53}	9.385	(0.00)***
α_{54}	0.061	(0.01)**	β_{54}	-0.029	(0.00)***
α_{55}	0.265	(0.00)***	β_{55}	0.957	(0.00)***

4.5 Magnitude of Volatility Spillovers between ETPs and Underlying

The magnitude of volatility spillover is the summation of the parameters of ARCH effects and GARCH effect in the BEKK model. The value of magnitude does not matter a lot, while the difference in magnitude represents the rank of contribution. In Table 4.15, the findings show that the contribution of volatility spillover from the nearby futures contracts to ETPs, given they are single commodity based ETPs, is higher than that from other. For example, the contribution of volatility spillover from the C1 to CORN_ETP is higher than that from C3. Similarly, W1 contributes more than W2 and W3 to the volatility of WEAT_ETP. On the other hand, the contribution from ETPs to underlying does not have a clear trend. For example, CORN_ETP has more volatility spillover effects on C2 than C1 and C3, while WEAT_ETP only affects the volatility of W3. In addition, the findings also show that corn futures and soybean futures contribute to the volatility spillover to JJG_ETP, in which soybean futures performs higher than corn futures. Similarly, JJG_ETP contributes more to soybean futures than corn futures in terms of volatility spillovers. With regard to DAG_ETP and underlying, the findings show that volatility contribution from sugar futures to DAG_ETP is higher than others while the volatility contribution from DAG_ETP to soybean futures is much higher than to other underlying commodities.

Table 4.15: Magnitude of Volatility Spillover Effects between ETPs and Underlying

Table 4.15 presents the magnitudes of agricultural ETPs and their underlying commodities. The expression of $\alpha_{ij}^2 + \beta_{ij}^2$ (i=1, 2...k; j=1, 2...k) is the summation of the squared parameters of ARCH effects and GARCH effects in the BEKK model.

Table 4.15

CORN_ETP and Underlying		SOYB_ETP and Underlying		WEAT_ETP and Underlying	
$\alpha_{14}^2 + \beta_{14}^2$	1.3*E-4	$\alpha_{14}^2 + \beta_{14}^2$	1.7*E-5	$\alpha_{14}^2 + \beta_{14}^2$	4.5*E-5
$\alpha_{34}^2 + \beta_{34}^2$	6.0*E-5			$\alpha_{24}^2 + \beta_{24}^2$	1.6*E-5
$\alpha_{41}^2 + \beta_{41}^2$	140.574			$\alpha_{34}^2 + \beta_{34}^2$	1.6*E-5
$\alpha_{42}^2 + \beta_{42}^2$	145.558			$\alpha_{43}^2 + \beta_{43}^2$	7.613
$\alpha_{43}^2 + \beta_{43}^2$	0.999				
JJG_ETP and Underlying		**DAG_ETP and Underlying**			
$\alpha_{15}^2 + \beta_{15}^2$	5.0*E-6	$\alpha_{25}^2 + \beta_{25}^2$	8.0*E-5		
$\alpha_{25}^2 + \beta_{25}^2$	9.0*E-6	$\alpha_{45}^2 + \beta_{45}^2$	7.3*E-4		
$\alpha_{51}^2 + \beta_{51}^2$	5.608	$\alpha_{51}^2 + \beta_{51}^2$	1.811		
$\alpha_{52}^2 + \beta_{52}^2$	100.829	$\alpha_{53}^2 + \beta_{53}^2$	396.889		
		$\alpha_{54}^2 + \beta_{54}^2$	0.005		

CHAPTER 5 CONCLUSIONS

This study aims to investigate the price discovery and volatility spillover effects between agricultural grain ETPs and their underlying, which are traded in different markets: the stock markets and the futures markets. Three types of potential results are assumed: 1) there exists bidirectional price and volatility transmission among ETPs and underlying components, 2) there exists unidirectional price and volatility transmission among ETPs and underlying components, 3) there does not exists directional price and volatility transmission among ETPs and underlying components. An additional purpose is assumed: the agricultural ETP market has a rising information share in the price discovery of underlying commodities.

To achieve these goals, this study examines the five most popular agricultural ETPs: three of them are single commodity based ETPs with multiple futures contract months, and two of them are multiple commodity based ETPs with nearby contract months. Due to short history of agriculture ETPs, this study covers all the historical data of each ETP since inception. Among them, the longest trading history ranges from October 23rd, 2007 to March 14th 2016. All the data of the trading history of each ETPs is obtained from Yahoo Finance, while all the trading history of the underlying of ETPs, the commodity futures contracts, is gained from Quandl Database. Then, after data manipulation, all daily settlement price data is used. Considering the existence of cointegration, this study adopts Vector Error Correction Model (VEC model) to explore price discovery among ETPs and underlying components. Following that, we apply Hasbrouck's (1995) method to measure the information share of ETPs and underlying components. Lastly, we obtain residuals from each VEC model and apply them into Baba, Engle, Kraft, and Kroner model (BEKK model) to investigate the volatility spillover effects among ETPs and underlying components.

From the results of VEC model, this study uncovers that there are unidirectional and bidirectional price spillover effects existing between certain ETPs and underlying components in both long-term and short-term. Take the CORN_ETP for example. There are unilateral relationships from the CORN_ETP to C2 and C3 in the long run, while there are unilateral relationships from the CORN_ETP to C1 and C2 in the short run. Similarly, in the long run, there are unilateral relationships from the SOYB_ETP to S2 and S3 and a bilateral relationship between SOYB_ETP and S1, while there are unilateral relationships from S2 and S3 to SOYB_ETP in the short run. Furthermore, in the long run, there are unilateral relationships from the WEAT_ETP to W1 and from W2 to WEAT_ETP, as well as a bilateral relationship between WEAT_ETP and W3, while there is no evidence of equilibrium relationships between WEAT_ETP and its underlying commodities in the short run.

With regard to JJG_ETP and DAG_ETP, there are unilateral relationships from JJG_ETP to corn futures and Kansas wheat futures in the long run, while there are strong unilateral relationships from JJG_ETP to corn futures and Kansas wheat futures. In addition, in the long run, there is a unilateral relationship from corn futures to DAG_ETP, while there are unilateral relationships from corn futures and wheat futures to DAG_ETP in the short run.

From the results for information share, this study shows that the information share of ETPs' underlying is much higher than ETPs. This means underlying commodities move faster than ETPs when new information comes. Interestingly, in three single commodity based ETPs, all the nearby futures contracts have the largest information share. This findings explains that they have more price discovery and move faster than others when new shocks come in the market. In addition, this study rejects the hypothesis that the agricultural ETPs have a rising information share in the process of price discovery.

From the results of BEKK model, this study finds that there indeed are unidirectional and bilateral volatility spillover effects existing between certain ETPs and their underlying. Take the CORN_ETP for example. The findings show that there are bidirectional shock transmissions between the CORN_ETP and underlying of C1 and C3 and a unidirectional shock transmission from CORN_ETP to C2. Meanwhile, there are bidirectional volatility spillovers between the ETP of CORN and underlying of C1, C2 and C3. Similarly, this also applies to the SOYB_ETP and WEAT_ETP. There are a bi-directional shock transmissions between the SOYB_ETP and S1, and a unidirectional shock linkage from SOYB_ETP to S2. And unidirectional volatility spillovers effects exist from S1 and S3 to SOYB_ETP. In addition, there are bi-directional shock transmissions between the ETP_WEAT and its underlying of W2, W3, and a unidirectional shock transmission from W1 to WEAT_ETP. The above findings imply the evidence of bi-directional volatility spillovers between the WEAT_ETP and W3 and unilateral volatility spillovers from W1 and W2 to WEAT_ETP.

With regard to JJG_ETP and DAG_ETP, this study uncovers evidences of bi-directional shock transmissions between the JJG_ETP and corn futures and soybean futures and unidirectional shock transmissions from Chicago wheat futures and Kansas wheat futures to JJG_ETP. And there are strong volatility transmissions from JJG_ETP to the corn futures and soybean futures. Thus, it concludes that there are bidirectional volatility spillovers effect existing between JJG_ETP and corn futures and soybean futures. In addition, there exist bi-directional shock transmissions between the DAG_ETP and wheat futures as well as sugar futures, and unidirectional shock transmissions from DAG_ETP to corn futures as well as soybean futures. Bidirectional volatility spillovers exist between the DAG_ETP and corn futures as well as sugar futures, and unilateral volatility spillovers from DAG_ETP to soybean futures and from wheat futures to DAG_ETP.

In the comparison of magnitude to volatility spillover effects, we find that the contribution of volatility spillovers from the underlying to ETPs and ETPs to the underlying. When they are single commodity based ETPs, the contributions of nearby futures contract are always higher than that from distant contracts. However, contributions from ETPs to underlying do not have a clear trend.

Due to limitations and time constraints, this study does not cover different methods of price discovery and volatility spillover measurements and other related factors. Further studies could analyze the volatility spillover effect between agriculture ETPs and their underlying commodities by focusing on the structural break (different time periods) in multivariate GARCH models, in addition to developing optimal hedging strategies using agriculture ETPs that could be adopted by investors.

REFERENCES

Aber, Jack W., Dan Li, and Luc Can. "Price volatility and tracking ability of ETFs." Journal of Asset Management 10.4 (2009): 210-221.

Ascioglu A., M. Aydogdu, R. K. Chou and L. P. Kugele (2006). "An Analysis of Intraday Patterns in ETF and Common Stock Spreads", working paper.

Ackert L. F. and Y. S. Tian (2000). "Arbitrage and Valuation in the Market for Standard and Poor's Depositary Receipts", Financial Management, v29, 71-87.

Bodie, Zvi. (1995). On the risk of stocks in the long run. Financial Analysts Journal 51, 18-22.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi. Do ETFs increase volatility? No.w20071. National Bureau of Economic Research, 2014.

Borkovec M, Domowitz I, Serbin V, et al. Liquidity and Price Discovery in Exchange-Traded Funds: One of Several Possible Lessons from the Flash Crash [J]. The Journal of Index Investing, 2010, 1(2): 24-42.]

Buguk, Cumhur, Darren Hudson, and Terry Hanson. "Price volatility Spillover in Agricultural Markets: an Examination of US Catfish Markets." Journal of Agricultural and Resource Economics (2003): 86-99.

Corbet Shaen, and Cian Twomey. "Have Exchange Traded Funds Influenced Commodity Market Volatility?" International Journal of Economics and Financial Issues 4.2 (2014): 323-335.

DeFusco, A.R, Ivanov I.S. and Karels V. G. (2011). The Exchange Traded Funds' Pricing

Deviation: Analysis and Forecasts. Journal of Economics and Finance, 35, 181-197.

Deville, Laurent. "Exchange Traded Funds: History, Trading and Research." Handbook of Financial Engineering. Springer US, 2008. 67-98.

Du, Xiaodong, Yu, Cindy L., & Hayes, Dermot J. (2011). Speculation and volatility spillover in the crude oil and agricultural commodity markets: A Bayesian Analysis. Energy Economics, 33(3), 497-503.

Engle, Robert, and Debojyoti Sarkar. "Premiums-discounts and exchange traded funds." Journal Of Derivatives 13.4 (2006): 27.

Figuerola-Ferretti I, Gonzalo J. Modelling and measuring price discovery in commodity Markets [J]. Journal of Econometrics, 2010, 158(1): 95-107.

Hamilton, James D., and Jing Cynthia Wu. "Effects of Index? Fund Investing On Commodity Futures Prices." International Economic Review 56.1 (2015): 187-205.

Hasbrouck J. One security, many markets: Determining the contributions to price discovery [J]. The journal of Finance, 1995, 50(4): 1175-1199.

Henker, Thomas, and Martin Martens. "Price discovery in HOLDR security baskets and the Underlying stocks." Available at SSRN 924520 (2006).

Krause, Timothy, and Yiuman Tse. "Volatility and return spillovers in Canadian and US industry ETFs." International Review of Economics & Finance 25 (2013): 244-259.

Li, Yanan, & Giles, David E. (2013). Modelling Volatility Spillover Effects Between Developed Stock Markets and Asian Emerging Stock Markets.

Lin, Ching-Chung, and Min-Hsien Chiang. "Volatility effect of ETFs on the constituents of the Underlying Taiwan 50 Index." Applied Financial Economics 15.18 (2005): 1315-1322.

Madura J. and N. Richie (2005). "Impact of the QQQ on Liquidity, Pricing Efficiency, and Risk Of the Underlying Stocks", working paper, Susquehanna University.

Noman, Abdullah M., and M. Nakibur Rahman. "Commodity futures indexes and related Exchange traded notes: Linear and nonlinear adjustment." Journal of Derivatives & Hedge Funds 19.3 (2013): 189-207.

Park T. H. and Switzer L. N. (1995). "Index Participation Units and the Performance of Index Futures Markets, Evidence from the Toronto 35 Index Participation Units Market", Journal of Futures Markets, v15, 187-2000.

Serra, Teresa. (2011). Volatility spillovers between food and energy markets: A semiparametric Approach. Energy Economics, 33(6), 1155-1164.

Yang J, Leatham D J. Price discovery in wheat futures markets [J]. Journal of Agricultural and Applied Economics, 1999, 31(02): 359-370.

Yang, Jian, Jin Zhang, and David J. Leatham. "Price and volatility transmission in international wheat futures markets." Annals of Economics and Finance 4 (2003): 37-50.

Yang, Jian, David Bessler, and David J. Leatham. "Asset storability and price discovery of Commodity futures markets: A new look." Available at SSRN 322682 (2002).

Yan, Bingcheng, and Eric Zivot. "A structural analysis of price discovery measures." Journal of Financial Markets 13.1 (2010): 1-19.

Zhao, Jieyuan, and Barry Goodwin. "Volatility spillovers in agricultural commodity markets: An Application involving implied volatilities from options markets." Selected Paper prepared for presentation at the AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, and July. 2011.