ESSAYS ON COMMODITY DYNAMICS, VOLATILITY, AND INTERACTION

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Contents

Summary

This thesis consisting of three self-contained essays devotes to the volatility behavior of agricultural commodity, price transmission between energy price and grain price and the extreme returns interaction and response among commodities.

The first essay investigates the persistence and permanent-transitory structure in the volatility of agricultural commodity continuous future contract returns with sample period from Jan 3^{rd}, 1994 to Feb 18^{th}, 2015. Lo's Modified R/S Test and GPH Test confirm the existence of volatility persistence in the whole sample period with both standard GARCH and component GARCH models with normal distribution, student-t distribution, generalized error distribution and skewed generalized error distribution. Component GARCH model finds strong evidence on the permanent-transitory structure. Out of sample forecasting with rolling estimation is performed together with Value at Risk backtesting. Out of sample forecasting superiority of component GARCH model is confirmed by both Diebold-Mariano test besides traditional loss functions and MZ regression. Risk management application also appears to favor component GARCH model. These findings suggest the necessity of modeling long memory in volatility of agricultural commodity for volatility forecast purpose and risk management purpose for policy makers and investor.

The second essay examines the asymmetry in price transmission between global grain and energy indices from January of 2007 to June of 2015. It applies nonlinear cointegration methods and its error correction model proposed by Sun (2011) together with the traditional linear methods. All methods confirm the existence with co-integration with high statistical significance. Nonlinear cointegration method also finds evidence on asymmetry and threshold effect in the price transmission. The existing literature

has mixed finding regarding the co-integration between grain and energy prices and this paper contributes by suggesting the failure to establish co-integration may lie in the model misspecification in ignoring asymmetry and threshold effect.

The third essay focuses on the extreme returns and responses in the commodity future market from an information flow perspective. It aims to examine whether there is heterogeneity in the interaction between extreme returns and those with the full samples. It applies modified event studies with bootstrapping to track the behavior of commodity future returns of Brent oil, corn, ethanol, natural gas, sugar and WTI oil around the extremely good and bad days defined by the returns of these commodities from Jan 1st, 1994 to Dec 31st, 2015. It also compares the result with those from generalized impulse response functions (IRFs). It finds evidence suggesting that the tail behaviors are distinct from those in the whole return spectrum and even among those tail behavior there is heterogeneity of many kinds.

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Abbreviations

1	first person
ACF	Auto-correlation function
ADF	Augmented Dickey–Fuller
AIC	Akaike information criterion
API	Application programming interface
ARCH	Autoregressive conditional heteroskedasticity
ARDL	Autoregressive distributed lag
ARFIMA	Autoregressive integrated moving average
BIC	Bayesian information criterion
CBOT	Chicago Board of Trade
CGE	Computable general equilibrium
CPI	Consumer Price Index
CTA	Commodity trading advisor
ECM	Error correction model
EMH	Efficient market hypothesis
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GBM	Geometric brownian motion
GIRF	Generalized impulse response function
ICE	Intercontinental Exchange
MAE	Mean of absolute errors
MSE	mean of square errors
MTA	Momentum Threshold Autoregression

NASA	National Aeronautics and Space Administration
NLS	Non-linear least squares
NYMEX	New York Mercantile Exchange
OPEC	Organization of the Petroleum Exporting Countries
PAM	Partial adjustment model
RFA	Renewable Fuels Association
RSM	Regime switching model
SPR	Strategic Petroleum Reserve
TAR	Threshold autoregressive
VAR	Vector autoregression
VaR	Value at Risk
VECM	Vector error correction model
WTI	West Texas Intermediate

Chapter 1

Introduction and Background

Commodities not only have impacts on the global economy, economic development, and social welfare both in history and in modern times, they also become an increasingly important asset class for investment and portfolio diversification purposes. Commodities are traded in spot market or with financial derivatives. With the former, delivery is scheduled immediately or with a minimum lag while the latter specifies the delivery of a commodity of certain quality at a fixed future date and location at a prespecified price. Future market facilitates price discovery and transfer of risk exposure as the most cited functions in the literature. Nowadays participants such as hedgers, speculators and arbitragers are actively involved in the future market due to its high liquidity, low transaction costs on the exchange and its absence of counterparty risk. No arbitrage argument can establish a relation between spot prices and future prices[1]. Both of spot prices and future prices are subject to respective market forces and shocks. The information content regarding price discovery and the causal link between spot prices and future prices have been of interest to academia (For examples, Figuerola-Ferretti and Gonzalo, 2010; Garbade and Silber, 1983; Gonzalo and Granger, 1995; Hasbrouck, 1995; Stein, 1961). The commodity market has been cited for its increased volatility and cross-correlations among different commodities partially because of shocks and increased interaction brought by financialization (Carter, Rausser, and Smith, 2011; Cheng and

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[1] For example, cash and carry arbitrage for storable commodity asserts that the spread of future price over spot price must equal the carrying cost of inventory (including the cost of financing the physical commodity, storage and insurance) net benefit from carrying physical commodity.

Xiong, 2014). Financialization of commodity refers to the phenomenon that commodity futures are becoming an asset class similar to equity and fixed income securities. For example, an investor has suffered loss from assets other than commodity future in her portfolio may consider to rebalance and adjust the positions in commodities. Besides, the nature of commodity products gives rise to substitution and complementarity in supply and demand of commodities (Carter et al., 2011). For example, agricultural commodities serve as the most prominent example for supply substitutability while grain feed for meat production stands for complements. Energy affects agriculture production since some inputs for agriculture production such as fertilizer and pesticides are petroleum based. Transportation for all commodities requires energy as well; especially, the recent surge of biofuel production also adds to the complication of the grain energy nexus.

Among all the commodities, crude oil plays an major role in global trade and economy, attracting attention from media, public citizens, policy makers, as well as academia. According to 2014 International Trade Statistics Yearbook United Nations (2015), petroleum oils and oils obtained from bituminous minerals (crude) are the top exported commodity in 2014 with 7.7% in value of total exports followed by petroleum oils and oils obtained from bituminous minerals (not crude) with 5.1%. For crude and refined product combined, there is 2.4 trillion value of trade per annual. The huge share of trade by value renders oil price essential to the economy of both oil exporting and importing countries. Besides taking the largest share in the global trade in value, crude oil is fundamentally different from other goods and services for several reasons. First, oil price increase usually is sharp and persistent in time, unlike other goods and service. Second, the demand for energy consumption is believed to be relatively inelastic compared to other goods and service. Third, the oil price is potentially influenced by some political events and military conflicts. The consequential production disruption is believed to be exogenous to the economy. Fourth, considerable concerns have arisen, and political actions have been taken about the environmental cost of crude oil consumption on a global scale. Finally, among all the commodities, energy commodities are believed to have the closest relationship to the real macroeconomic performance, which is evidenced by the seemingly subsequent economic recessions following the dramatic increases in oil price.

As documented by Barsky and Kilian (2004), since the 1970s most of the historical macroeconomic recessions have been preceded by political events in the Middle East such as 1973 War and Oil Embargo, 1980 Iranian Revolution, 1981 Iran-Iraq War and 1990 Invasion of Kuwait. All these events are believed to be responsible for the subsequent increases in the oil price. Besides, the high oil prices are also blamed for the productivity slowdown as measured by the growth in total factor productivity in the 1970s, which is backed up by their statistical association. Commodities ranging from fuel, metals and agricultural are used as input for industrial production as well as household consumption. However, not all exogenous oil event have impacts on CPI, and large spikes of the CPI inflation are apparently not necessarily related to oil events. For the association of the real oil price and US recession, there are long and varying lags between the cited political conflicts and the subsequent recessions. These irregular lengths of delays question the mechanism of how spikes in oil price cause the recessions. Besides, Barsky and Kilian (2004) challenged the perception that the U.S. stagflation of the 1970s is caused only by the oil crisis, which is perhaps the most striking record of price change after World War II.

Barsky and Kilian (2004) and Kilian (2008) review several mechanisms providing with a causal link from oil price to recessions, inflation and economic slowdown. The mechanisms of transmission by which oil price affect the economy fall into two categories: supply and demand channels. The supply channel focuses on the production process with a value added production function where imported crude oil is used as an intermediate input. However, these models suffer from the contradiction between interpreting crude oil as an intermediate input and the net importation of crude oil. Besides, from the theoretical perspective, production-based models that bound the impacts on domestic output by the oil cost share fail to explain the huge fluctuation in real output. The remedy for these two shortcomings is proposed such as time-varying markups and models with capital-energy complementarities in the production but empirical evidences supports none of them. The demand channel pointed out in Hamilton (2008) as the key mechanism works through the disruption of spending of consumer and firm on goods and services apart from energy. The empirical support and economic rationale are also documented in Kilian (2008). Energy price affects consumption expenditure through four complementary mechanisms. First, discretionary income effect asserts higher energy price reduces the money spent on other goods and service. Second, uncertainty effect is that the increased uncertainty about the future energy price results in postponement of purchase of consumer durable goods. Third, precautionary savings effect focuses on the consumers smoothing their consumption due to the perceived greater likelihood of future loss in income. Lastly, operation cost effect limits to cases where consumers delay or forego the purchase of energy-related durable. Another channel in demand side theory is through non-residential investment. When faced with decisions regarding investment expenditures, firms are also affected by energy prices through two mechanisms: raise in the energy price increases the marginal cost of the production; firms cut investment in equipment and infrastructures when they anticipate any reduced demand. Regarding these channels, there is empirical evidence showing diminishing impacts of oil on the U.S. economy (Edelstein and Kilian, 2007). Edelstein and Kilian (2007) separate the data into two halves, 1970.2-1987.12 and 1988.1-2006.7. They find out that energy price shocks have diminished impacts on consumption aggregates since the mid-1980s and attribute this change to changes in the composition of U.S. automobile production towards more energy-efficient. Besides, the U.S. automobile sector has become less important in terms of shares of domestically produced automobiles and employment shares.

So what is oil shock and where do they come from? Oil price shocks are the difference between the expected oil prices and the actual prices. Baumeister and Kilian (2016) summarize the potential sources of oil price fluctuation:

> “determinants including 1) shocks to global crude oil production arising from political events in oil-producing countries, the discovery of new fields and improvements in the technology of extracting crude oil; 2) shocks to the demand for crude oil associated with unexpected changes in the global business cycle; 3) and shocks to the demand for above-ground oil inventories, reflecting shifts in expectations about future shortfalls of supply relative to demand in the global oil market.”

These three categories focus on the fundamentals of the crude oil production with the first point related to the supply side and the last two points involving the demand side. The supply of oil consists of the current production as well as the potential avilability in the future. The former can be affected by the exogenous political events in oil producing countries, although production decision by OPEC can be considered endogenous and in some sense predictable. The latter concerns the availability of crude oil underground. The proven crude oil reserves usually measure the crude oil availability. It refers to the "the estimated quantities of all liquids statistically defined as crude oil. They consist of those quantities of crude oil which by analysis of geoscience and engineering data can be estimated with reasonable certainty to be commercially recoverable, from a given date forward, from known reservoirs and under defined economic conditions, operating methods and government regulations" (OPEC, 2015). Technical and economical recoverability at the current price level of crude oil and with current extracting technology are essential in this definition. Thus sharp technology breakthrough of mining technique can also have impacts on the oil availability.

Alquist, Kilian, and Vigfusson (2013) cover in the handbook chapter many aspects on crude oil price forecasting. It includes the choice of sample period, oil price alternative series, model specification, real or nominal price, predictability based on macro aggregates, information content of oil futures, and usefulness of survey forecast. They conclude that even the best available forecasting methods are far from satisfactory regarding forecast accuracy. In fact, the oil price can only be predicted as accurately as their determinants can be. Baumeister and Kilian (2016) document the difficulty in forecasting the fluctuation of oil price rises from the three categories of shocks. As for oil production, constant production disruption is always unpredictable. Moreover, production responds to the price changes by launching new oil field search whose success is hard to predict with unknown forthcoming time. Besides, in the long run, demand for fossil fuel can be replaced by the substitutes such as renewable the same way as coal was replaced. Demand for all commodity driven by global business cycle depends on the condition of the global economy. However, state of the global economy can be only predicted in short horizons with far from satisfactory accuracy with econometric model and for professional forecasters. Last but not least, the change in the perceptions about the future scarcity of oil adds to the uncertainty. The changes in prospects for global economy and evolution of geopolitics shift the precautionary demand for oil even more rapidly in the form of inventory of oil above ground. Historical evidence shows it requires both anticipated shortfall of supply and anticipated demand to drive such precautionary demand.

These three kinds of shocks have different impacts on the economy. As pointed out in Kilian (2009), evaluating impacts of an exogenous oil shock on the economy is a thought experiment since the impact of oil price is evaluated with all else equal. This thought experiment cannot be defined properly due to both potential reverse causality and the mixture of direct and indirect impacts of global economy demand shocks on US economy. Specifically, oil price is mainly driven by the fundamentals. Thus, not only the oil price changes have an impact on the US economy but also the US macroeconomic condition drive the oil price through demand. Moreover, the global economy is affecting the demostic economy directly and indirectly through the oil price. Kilian (2009) proposes a structural VAR model to tackle the above two issues simultaneously. In his paper, the global crude shocks are decomposed into three components: crude oil supply shocks; global demand shock to all industrial commodities; and demand shock specific to crude oil. The last one captures the precautionary demand resulted from the uncertainty of any future availability of oil supply and it represents the convenience yield of accessibility of crude oil inventory. To facilitate this decomposition, a weighted index on dry cargo voyage ocean freight rates is constructed to capture the aggregate demand for all commodity while crude oil production and real oil price are also used. Controlling both the oil production and global demand for all industrial commodities enables the residuals to capture the oil-specific demand. Historical oil shocks are found to consist mainly of the global aggregate demand shocks and precautionary demand shocks but not supply shocks. The finding challenges the traditional wisdom that links the sharp oil price surges and disruption of oil production due to exogenous political events. The increased precautionary demand for oil matters more for the increases in oil price than the drop in physical supply of oil does. The analysis helps explain the absence of major recession in the US after the sharp increase in oil price since 2003 versus the recession following 1970s oil crisis. The former is driven by the booming global economy whereas the latter is fueled by the disruption of oil production as well as the consequential increase in precautionary demand.

Agricultural commodity has become increasingly interconnected to crude oil. Despite its small share of the global economy, agriculture production engages 1.3 billion out of 7.1 billion population (equivalent to 19%) in 2012 according to World Bank (2012) and occupies 40% of the land area. Besides, grain is the main source for calorie for human. Similar to crude oil, agricultural commodity price dynamics is mainly driven by its fundamentals with seasonal fluctuations. However, in the past ten years, global grain markets of rice, wheat and corn have experienced sharp increases. Given the importance of agricultural commodity, the welfare implication, and the distributional effect among the market participants, this abrupt increase in prices has attracted attention from consumers, producers, and policy makers. Wright (2014) reviews the possible contributing factors:

> *"unprecedented increases of income of the vast populations consumption caused by unprecedented increases of income of the vast populations of China and India; idiosyncratic regional droughts and fires; speculative bubbles; a of China and India; idiosyncratic regional droughts and fires; speculative bubbles; a new 'financialization' of grain markets; the slowdown of global agricultural research new 'financialization' of grain markets; the slowdown of global agricultural research spending; jumps in costs of energy and fertilizers; shifts in interest rates; the decline spending; jumps in costs of energy and fertilizers; shifts in interest rates; the decline of the dollar; the surge in biofuel demands; bans on genetically modified plants; of the dollar; the surge in biofuels demands; bans on genetically modified plants; and climate change."*

Historically, the price and production of grain are well explained by a basic Marshallian model of demand and supply with inter-grain substitution (substitution of one grain for another) and inter-temporal substitution (storage enables substitution of current consumption for future consumption) until 2004. Wright (2014) attributes this lack of explanatory power since 2004 to the missing role of biofuel production surge. In his paper, the additional substitution of biofuel for petroleum-based fuel together with the inter-grain substitution and inter-temporal substitution explains the annual fluctuations in the price and production well. As he points out, the surge of the biofuel production is partially policy driven. The US and EU increased the limit of the ratio of biofuel in blends with products derived from fossil fuel such as gasoline and implemented a mandate regarding the use of biofuel in transport fuel in addition to policy on subsidy and tariff. This policy change met with the dramatic increase in oil price and thus amplified the effect of this biofuel substitution. With this mechanism, it should be expected that energy price will have an impact on the grain price.

Common driving forces stemming from the global business cycle and interconnection arising from the nature of the commodities increase the interaction and the volatility of commodity returns. With this increased complexity in the dynamics and interaction, existing literature has been devoted to dynamics and interaction between grains and fossil fuel. Despite the popularity of conditional volatility model gained in the others asset classes, limited attention has been paid to agricultural commodity. Among them, Giot (2003) combines the implied volatility with conditional volatility to examine the incremental information content of implied volatility to GARCH models for cocoa, coffee, and sugar futures. Onour and Sergi (2011) compare two competing GARCH models with normal distribution and student-t distribution. While agricultural commodity volatility exhibits long memory behavior, not many studies devote to it even though standard GARCH model is theretically inconsistent with this characteristic. Three crude oil markets - Brent, Dubai, and West Texas Intermediate (WTI) are found better captured by CGARCH and FIGARCH than by GARCH and IGARCH (Kang, Kang, and Yoon, 2009). Jin and Frechette (2004) study fractional integration of volatility process for fourteen agricultural future series and compare the forecasting performance with GARCH model and find out FIGARCH out-performs. Chang, Mcaleer, and Tansuchat (2012b) find that FIGARCH outperforms the GARCH counterpart, and fractional integration exists in most of agricultural commodity futures returns series. Engle and Lee (1999) argue that long memory behavior in volatility is caused by the changing level of unconditional volatility. Therefore they propose Component GARCH (CGARCH) model which decomposes conditional variance into two components in an additive form. The one with nearly unit root is termed long-run (permanent) component, which is allowed to evolve slowly in an auto regressive way. The other component with a much more rapid decay rate is called short-run (transitory) volatility component. The first essay aims to investigate the persistence of volatility dynamics and permanent-transitory structure of agricultural commodities by employing CGARCH and GARCH models. Parametric and semi-parametric methods confirm the existence of volatility persistence and CGARCH model finds strong evidence on the permanent-transitory structure. Out of sample forecasting superiority of CGARCH is also confirmed by both Diebold-Mariano test and risk management application besides traditional loss functions.

The increased complexity arising from the proliferation of biofuel also stimulate the research on energy-agricultural price linkage. Most of empirical papers mainly utilize cointegration and the finding regarding the price series interaction is mixed. Most authors find that evidence on biofuel or energy price affecting feedstock prices in the long run with both local or international data ranging from quarterly data to daily data (Balcombe and Rapsomanikis, 2008; Busse, Brümmer, and Ihle, 2012; Campiche, Bryant, Richardson, and Outlaw, 2007; Ciaian and Kancs, 2011a,1, among others) while other do not (Hassouneh, Serra, Goodwin, and Gil, 2012; Mallory, Irwin, and Hayes, 2012; Qiu, Colson, Escalante, and Wetzstein, 2012; Yu, Bessler, and Fuller, 2006; Zhang and Reed, 2008). Enders and Granger (1998) point out that unit roots and cointegration tests have low power to detect unit roots or cointegration with asymmetric adjustment. The failure of some of the existing literature to detect cointegration could be due to the inability to take care of the asymmetry. Thus the second essay examines the asymmetry with nonlinear cointegration methods by Enders and Siklos (2001) and its error correction model proposed by Sun (2011). It finds strong evidence on the asymmetry in nonlinear cointegration with threshold effects. This chapter thus provides a plausible explanation for the mixed finding regarding energy-agricultural price linkage.

The cross-commodity dynamics interactions usually do not distinguish the interaction in the tail or extreme returns from those with the full samples. Neither the behavior of returns around extreme returns of cross-commodity have been studied in the literature. The extreme return interaction is of both theoretical interest and practical implication. In the third essay, a modified event study methodology with bootstrap inference is applied to track the behavior of commodity returns of Brent oil, corn, ethanol, natural gas, sugar and WTI oil around the extremely good and bad days defined by the returns of these commodities. It finds evidence suggesting that the tail behaviors are distinct from those in the whole return spectrum and even among those tail behavior there are heterogeneity of many kinds.

The thesis consists of five chapters. The second chapter devotes to the long memory volatility of agricultural commodity. The third chapter focuses on the nonlinearity of energy grain nexus. The fourth chapter is about extreme return interaction of commodities. The last chapter concludes this thesis.

Chapter 2

Essay One: Long Memory Volatility in Food Futures

2.1 Introduction

Accurately characterizing and capturing volatility is of great interest to financial economists as well as financial practitioners. Although volatility is not the same as risk, it is perceived as uncertainty. It plays an important role in many financial applications Poon and Granger (2003). Specifically, volatility is applied in risk management, asset allocation, derivative pricing and decisions related to volatility level such as volatility trading. For volatility modeling, there are two branches of volatility models. Stochastic volatility model specifies volatility to be a stochastic process evolving due to random shocks while conditional volatility model specifies volatility to be time varying in an autoregressive manner. However, the former branch of models usually does not have closed form solution for likelihood function, which makes the estimation process more complex. Conditional volatility modeled by Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (Bollerslev, 1986) specifies conditional variance to be a linear combination of the lagged conditional variances and lagged squared shocks. The conditional variance mean-reverts to its unconditional level. GARCH model manages to explain volatility clustering and fat tail behavior observed in the unconditional return distributions in return series of many assets. Besides, many extensions on conditional volatility have been proposed to capture the other stylized facts of the return such as asymmetry and long persistence.

Only limited papers have been devoted to agricultural commodity conditional volatility modeling compared to popularity conditional volatility models have gained in equity, currency, fixed income, and commodity other than agricultural commodities probably due to the fact that agricultural commodity used to be less volatile. However, agricultural commodity modeling should interest not only academia and practitioners but also politicians and policy makers especially after the global food crisis during 2007-2008 with dramatic increase price has harmed those net food importing countries. The most striking stylized fact of financial asset return volatility is volatility clustering, which mean return volatility is positively autocorrelated. Changes in volatility can result from the arrival of information or news, which brings uncertainty. Long memory volatility characteristic has been studied in foreign exchange market and the arrival of heterogeneous information and heterogeneous traders with different time horizons has been proposed for an explanation. Under heterogeneous information, short-lived information arrives and decays over intra-day frequency and long-lived information dies out during both in high and low frequencies. Therefore the aggregated long memory dependency could be observed in the lower frequency domain (Andersen and Bollerslev, 1997). Alternatively, the explanation of heterogeneous traders argues that traders with different position holding periods or investment horizons evaluate the market at different frequencies and thus generate both long and short term components in the volatility process (Muller, Dacorogna, Dave, Olsen, Pictet, and von Weizsäcker, 1997).

In the case of agricultural commodities, the fundamentals are the main drivers for the asset price changes. All the factors affecting current or anticipated future demand and supply will have an impact on the volatility. Unlike hard commodities which are usually natural resources and are mined or extracted, agricultural commodity products, as known as soft commodities, are grown. It takes time to plant and harvest for the production of agricultural product. Thus this nature potentially contributes to the long run dependence in the volatility observed in data. After testing for the existence of long memory behavior in the volatility, this chapter applies the component GARCH model (Engle and Lee, 1999) to capture the long memory behavior of returns of four agricultural future contracts and examines the permanent and transitory components. The volatility modeling is later companioned with the risk management application and back-testing. This chapter confirms the existence of permanent and transitory components in volatility process and the superior performance of component GARCH model in term of out of sample forecast and risk management application. It suggests that the long memory volatility behavior of agricultural commodities should be better captured and modeled by the component GARCH model.

Different financial assets demonstrate different aspects of return characteristics. As "all models are wrong, but some are useful", models are only meant to capture particular aspects of the returns. Agricultural commodity received less attention due to their less volatility level until peak in the recent years. Motivated by the nature of agricultural commodity production, this chapter aims to study the long memory property of the conditional volatility. In order to avoid overfitting, this chapter uniquely applies out of sample risk management backtesting method and find out the superiority of capturing the long memory property.

In the next section, the related literature on agricultural volatility modeling and long memory volatility are reviewed. In section 3, methodology and models applied in this chapter are discussed. It is followed by the estimation result showing strong evidence of long memory behavior in the volatility of agricultural commodity returns and the out of sample forecasting superiority of CGARCH. The chapter ends with the conclusion and the potential contribution.

2.2 Review of Literature: Missing Role of Volatility Persistence in Agricultural Commodity

The definition of volatility depends on the content of discussions. It can refer to the parameter in the geometric Brownian motion (GBM) of the logarithm of asset price; historical volatility refers to the standard deviation of returns in the sample; conditional volatility specifies the standard deviation of a future return conditional on the information of previous returns; stochastic volatility, on the other hand, models the volatility as a stochastic process with random shocks; alternatively implied volatility is the volatility that equates the theoretical price based on a particular pricing model to the observed price of market traded derivative (Taylor, 2007). All of these methods find their places in the existing literature of agricultural commodity volatility modeling. Giot (2003) combines the implied volatility with conditional volatility to examine the incremental information content of implied volatility to GARCH models for cocoa, coffee, and sugar futures. The author finds out squared returns with only marginal improvements of the information content in implied volatility and value-at-risk (VaR) models with only implied volatility functions as well the ones with GARCH model. Focusing on conditional volatility model, Onour and Sergi (2011) compare two competing GARCH models with normal distribution and student-t distribution for rice, sugar, beef, coffee, and groundnut prices and find out the models with fat tail conditional distribution outperforms their counterparts with normal distribution. Besides, they specify the mean equation as an ARFIMA(p, d, q) model but leave the long memory in volatility out of examination.

Standard GARCH model assumes volatility reverts to a fixed long run unconditional volatility. However, for time series spanning for long time horizons, it is not reasonable to assume the unconditional volatility is fixed as the economic conditions or the fundamentals could have changed dramatically during the period under study. Besides, it fails to capture long memory behavior in the volatility dynamics for most of the financial assets. Specifically, standard GARCH model implies theoretical autocorrelations of both of conditional variances and squared returns are geometrically bounded, i.e. $|\rho_\tau| \leq C\phi^\tau$ for some constant $C > 0$ and $0 < \phi < 1$, while their empirical counterparts decay more slowly. Long memory, also known as persistence, refers to the phenomenon that the auto-correlation function (ACF) does not decay exponentially as suggested by standard GARCH, but at a slower rate. Engle and Lee (1999) argue that persistence is caused by the changing level of unconditional volatility. Therefore they propose Component GARCH (CGARCH) model which decomposes conditional variance into two components in an additive form. The one with nearly unit root is termed long-run (permanent) component, which is allowed to evolve slowly in an auto regressive way. The other component with a much more rapid decay rate is known as short-run (transitory) volatility component. Therefore CGARCH model is also called permanent-transitory component variance model. Besides CGARCH model, fractional integration GARCH (FIGARCH) proposed by Baillie, Bollerslev, and Mikkelsen (1996) also models volatility persistence by specifying fractional difference in the variance equation.

Modeling and forecasting volatility persistence have been extensively studied in foreign exchange market (Baillie et al., 1996; Conrad and Lamla, 2010) and equity markets (Bollerslev and Ole Mikkelsen, 1996; Degiannakis, 2004; Kang and Yoon, 2007). However, not many attention have been paid to commodity markets with few exceptions. Three crude oil markets - Brent, Dubai, and West Texas Intermediate (WTI) are found better captured by CGARCH and FIGARCH than by GARCH and IGARCH (Kang et al., 2009). CGARCH and FIGARCH also provide superior performance in out of sample volatility forecast based on forecast performance measures such as mean of square errors (MSE) and mean of absolute errors (MAE) as well as statistical tests such as Diebold and Mariano (1995) test. Barkoulas, Labys, and Onochie (1997) focus on commodity spot prices for aluminum, cocoa, coffee, copper, rice, and rubber. They show varying fractional orders across different type of the commodities. Long memory volatility modeling of agricultural commodity future is also studied in Chang et al. (2012b). They find that FIGARCH outperforms the GARCH counterpart, and fractional integration exists in most of the agricultural commodity futures returns series. Crato and Ray (2000) compare the volatility persistence of currency and commodity future and find that commodity volatility to be more persistent. Jin and Frechette (2004) study fractional integration of volatility process for fourteen agricultural future series and compare the forecasting performance with GARCH model and conclude that FIGARCH out-performs.

This chapter aims to investigate the persistence volatility dynamics of four agricultural commodities, namely corn, rice and wheat commodities continuous futures contracts traded on the Chicago Board of Trade (CBOT). CGARCH and GARCH models are employed with four conditional distributions to potentially capture the fat tail and skewness. It first confirms volatility persistence with parametric and semi-parametric methods. For out of sample forecast, it employs one day head rolling estimation and forecast. It also differs from the existing literature by evaluating the volatility forecast via both Diebold-Mariano test and risk management application besides traditional loss functions. By decomposing conditional volatility into long run and short run, CGARCH model with over twenty-year span of data casts light on the existence of permanent and transitory components of conditional variance.

2.3 Methodology

The empirical analysis consists of five steps. First, the returns and squared returns for long memory behavior are tested with parametric Lo's modified R/S test Lo (1991) and semi-parametric GPH test. Second, the return series are fitted with GARCH, and component GARCH models with conditionally normal, student, (skewed) generalized error distributions. For random variable ε following student distribution, its pdf is expressed as $f(\varepsilon) = \frac{\Gamma(\frac{\nu+1}{2})}{\sqrt{\beta\nu\pi}\Gamma(\frac{\nu}{2})}(1+\frac{(\varepsilon-\alpha)^2}{\beta\nu})^{-\frac{\nu+1}{2}}$ with α, β, and ν representing the location, scale and shape parameters respectively and Γ being the gamma function. For random variable ε following generalized error distribution, its pdf is expressed as $f(\varepsilon) = \frac{\kappa e^{-0.5|\frac{\varepsilon-\alpha}{\beta}|^{\kappa}}}{2^{1+\kappa^{-1}}\beta\Gamma(\kappa^{-1})}$ where α, β and κ are the location, scale and shape parameters. The skewness introduced by inverse scale factors γ for random variable ε gives pdf $f(\varepsilon|\gamma) = \frac{2}{\gamma+\gamma^{-1}}[f(\gamma\varepsilon)\boldsymbol{I}_{[0,\infty)}(\varepsilon)+f(\gamma^{-1}\varepsilon)\boldsymbol{I}_{(-\infty,0)}(\varepsilon)$ where $\boldsymbol{I}(\cdot)$ is an indicator function and $f(\varepsilon)$ is a pdf, which is unimodal and symmetric around 0. More formally, inverse scale factors $\gamma = 1$ degenerates the pdf $f(\varepsilon|\gamma) = f(\varepsilon)$ and $\frac{P(\varepsilon\geq 0|\gamma)}{P(\varepsilon<0|\gamma)} = \gamma^2$. Thus $\gamma > 1$ suggests right skewness and $\gamma < 1$ suggests left skewness. The optimal lags for each model are selected with each conditional distribution according to Schwartz Bayesian Criterion (SBC). The last 1500 observations are kept for out of sample forecasting with rolling estimation and one day ahead forecasting. The forecast performance is evaluated and compared between models with Diebold Mariano test Diebold and Mariano (1995). Volatility forecasting is also utilized in a value at risk (VaR) forecast and unconditional and conditional coverage test of Kupiec (1995) and Christoffersen (1998) are employed respectively to backtest the VaR forecast to examine the performance of the volatility modeling.

2.3.1 Parametric Lo's Modified R/S Test for Long Memory

Empirical non-exponentially decaying ACF only suggests but cannot confirm long memory behavior without a proper statistical test. The two common tests are parametric Lo's modified R/S test and semi-parametric GPH test. These two tests are employed in the analysis.

The famous rescaled range R/S statistic is proposed by Hurst (1951) to test long memory behavior of time series. It is defined with the partial summation of time series $\{r_t\}_{t=1}^{T}$

$$M_T = \max_{1 \leq t \leq T} \sum_{t=1}^{k} (r_j - \bar{r}) - \min_{1 \leq j \leq T} \sum_{t=1}^{k} (r_t - \bar{r})$$

where $\bar{r} = \frac{1}{T} \sum_{t=1}^{T} r_t$. The R/S statistic is expressed as follows:

$$\frac{R}{S} = \frac{1}{\sqrt{T}\hat{\sigma}} M_T$$

, where the partial summation is scaled by a multiple of sample standard deviation of the returns series. Lo (1991) argues the R/S statistic could be improved by replacing the sample standard deviation $\hat{\sigma} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(r_t - \bar{r})^2}$ by the square root of Newey-West estimate of the long run variance $\hat{\sigma} = s[1 + 2\sum_{j=1}^{q}(1 - \frac{j}{q+1})\hat{\rho}_j]^{\frac{1}{2}}$ where $\hat{\rho}_j$ is the sample autocorrelation of the returns. The optimal bandwidth q for estimation the long run variance is chosen as $\lfloor 4(T/100)^{1/4} \rfloor$, where $\lfloor \cdot \rfloor$ returns the integer part of the argument. Detailed explanation can be found in Zivot and Wang (2003).

2.3.2 Semi-parametric GPH Test for Long Memory

The fractionally integrated process can be expressed by a spectral density as follows (see Geweke and Porter-Hudak, 1983):

$$f(\omega) = [4\sin^2(\frac{\omega}{2})]^{-d} f_u(\omega)$$

where ω is the Fourier frequency, and $f_u(\omega)$ is the spectral density of the white noise series u_t. The GPH estimator of the fractional difference parameter d is based on least squares estimate $\hat{d}$ the following regression equation:

$$\ln(f(\omega_j) = \beta - d\ln[4\sin^2(\frac{\omega_j}{2})] + e_j$$

for $j = 1, 2, \cdots n_f(T)$, $n_f(T) = T^\alpha$ and $0 < \alpha < 1$. The least squares estimate $\hat{d}$ is normally distributed: $\hat{d} \sim N(d, \frac{\pi^2}{6\sum_{j=1}^{n_f}(U_j - \bar{U})^2})$, where $U_j = \ln[4\sin^2(\frac{\omega_j}{2})]$ and $\bar{U}$ is the sample mean for $\{U_j\}_{j=1}^{n_f}$.

2.3.3 GARCH Models

ARCH volatility modeling requires specification of mean equation and variance equation. After an auto-regressive moving average (ARMA) filtering of a series, the residuals of the mean equation are linear uncorrelated or of minor linear correlation, but still dependent. Therefore, the higher moments of the residuals could exhibit linear dependence and ARCH family models are to model the squared residuals from the mean equation.

In the general setting, mean equation can be expressed in the form of auto-regressive fractionally integrated moving average with exogenous inputs and volatility term model (ARFIMAX-ARCH-in-mean) as shown in Eq (1) and Eq.(2). where y_t is the series of interest and μ_t is the conditional mean of y_t, *i.e.* $\mu_t = E(y_t|\mathfrak{F}_{t-1})$. $\mathfrak{F}_{t-1}$ is the information set available at time $t-1$. $\varepsilon_t = y_t - \mu_t$ is called shocks or innovations representing new information arriving at time t, which is an unpredictable component. $(1-L)^d$ is a fractional differencing capturing the long memory effect in the conditional mean, where $0 < d < 1$. $\Phi(L)$ and $\Theta(L)$ are lag polynomials for auto-regressive and moving average representation respectively. For condition mean equation in Eq.(2), $\{x_{i,t}\}_{i=1}^m$ are m exogenous variables, n of which have cross product terms with volatility σ_t. The last term is ARCH-in-mean term, *i.e.*, $\xi\sigma_t^k$ where k can be 1 or 2, representing conditional standard deviation or conditional variance respectively. The shocks or innovations are generated by scaling a normalized random variable z_t with conditional standard deviation σ_t as shown in Eq.3. z_t is usually specified to follow a standardized distribution with mean 0 and variance 1.

$$\Phi(L)(1-L)^d(y_t-\mu_t)=\Theta(L)\varepsilon_t, \tag{1}$$

$$\mu_t=\mu+\sum_{i=1}^{m-n}\delta_i x_{i,t}+\sum_{i=m-n+1}^{m}\delta_i x_{i,t}\sigma_t+\xi\sigma_t^k, \tag{2}$$

The standard GARCH is proposed by Bollerslev (1986) and can be written as Eq.(4). σ_t^2 is the conditional variance[1] on the information available at $t-1$. The m external variables $\{v_{jt}\}_{j=1}^m$ are indexed t just for notation convenience. $\sum_{j=1}^q\alpha_j\varepsilon_{t-j}^2+\sum_{j=1}^p\beta_j\sigma_{t-j}^2$ are linear combination of lagged squared innovations and conditional variances. The unconditional variance of the model is calculated as $\sigma_u^2=\frac{\hat{\omega}}{1-\sum_{j=1}^q\alpha_j-\sum_{j=1}^p\beta_j}$.

$$\varepsilon_t=\sigma_t z_t, \qquad z_t\sim D(0,1) \tag{3}$$

$$\sigma_t^2=(\omega+\sum_{j=1}^m\zeta_j\nu_{jt})+\sum_{j=1}^q\alpha_j\varepsilon_{t-j}^2+\sum_{j=1}^p\beta_j\sigma_{t-j}^2 \tag{4}$$

Subtracting σ_u^2 from both sides of variance equation from GARCH yields

$$\sigma_t^2-\sigma_u^2=\sum_{j=1}^q\alpha_j(\varepsilon_{t-j}^2-\sigma_u^2)+\sum_{j=1}^p\beta_j(\sigma_{t-j}^2-\sigma_u^2) \tag{5}$$

The standard GARCH model implies conditional variance mean reverts to its unconditional variance σ_u^2. Persistence parameter defined as $\hat{P}=\sum_{j=1}^q\alpha_j+\sum_{j=1}^p\beta_j$ can be interpreted as mean reverting rate and half-life defined as $h2l=\frac{-\ln 2}{\ln\hat{P}}$ is the periods required for half of expected reversion back toward σ_u^2. For GARCH(1, 1), l steps ahead forecast at t can be expressed as $\hat{\sigma}_{t+l}^2=\sigma_u^2+(\alpha_1+\beta_1)^l(\sigma_t^2-\sigma_u^2)$.

For daily returns in our analysis, mean equation is specified as $\mu_t=0$ and variance equation is estimated with lags for squared shocks and conditional

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[1] Some researchers denote conditional variance as h_t such that $\varepsilon_t=z_t h_t^{1/2}$.

variance up to two, *i.e.* $p \in \{1,2\}$ and $q \in \{1,2\}$

$$\begin{aligned} r_t &= \varepsilon_t \\ \varepsilon_t &= \sigma_t z_t, \qquad z_t \sim D(0,1) \\ \sigma_t^2 &= \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \end{aligned}$$

2.3.4 Component GARCH

Engle and Lee (1999) argue that the persistence observed in the absolute returns and squared returns is due to the change in the long-run volatility. It is unreasonable to assume the unconditional variance σ_u^2 is fixed as in standard GARCH model. Engle and Lee (1999) replaces the unconditional variance σ_u^2 in Eq.5 with a so-called long run volatility q_t in Eq.8. The conditional variance is decomposed into a long run component q_t and a short run component s_t in Eq.(6). Under CGARCH specification, conditional variance mean reverts to its long run component q_t and the long run component evolves slowly in an auto-regressive way close to a unit root process.

$$\sigma_t^2 = q_t + s_t \tag{6}$$

$$s_t = \sum_{j=1}^{q} \alpha_j (\varepsilon_{t-j}^2 - q_{t-j}) + \sum_{j=1}^{p} \beta_j (\sigma_{t-j}^2 - q_{t-j}) \tag{7}$$

$$q_t = \omega + \eta_{11} q_{t-1} + \eta_{21}(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \tag{8}$$

Short run component can also be expressed in an auto-regressive form: $s_t = (\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j) s_{t-j} + \sum_{j=1}^{q} \alpha_j (\varepsilon_{t-j}^2 - q_{t-j})$. In component GARCH model, $\sum_{j=1}^{q} \alpha_j + \sum_{j=1}^{p} \beta_j$ and η_{11} define the persistence parameters in the short run and long run respectively.

2.3.5 Rolling estimation and out of sample forecasting

The returns in the last 1500 trading days, roughly equivalent to 6 calendar years, are kept for out of sample forecast evaluation. Models are first estimated with the data in the sample excluding the last 1500 days. Then optimal lags for both models are selected with different conditional distributions. In general, out of sample forecast can be made in two ways regarding to sample utilization: recursive windows and moving windows. Both methods estimate the specified model in the same sample of observations and conduct forecasts with the specified horizon. Unlike the moving windows methods recursive method drops the oldest observation when a new observation is added. In short, recursive windows keeps increasing the number of sample for estimation while moving windows keeps the numbers of sample fixed and moves the window forward for estimation. This chapter chooses moving windows method to keep the re-estimated models comparable.

2.3.6 Volatility Proxy and Forecast Direct and Indirect Evaluation

The key feature of the underlying volatility of assets returns is that volatility is unobservable, even *ex post.* For daily data, the mean equation for these series is not specified, and squared returns r_t^2 are used as volatility proxy[2] for conditional variance σ_t^2 forecast evaluation.

In the literature, Mincer Zarnowitz (MZ) regression (Mincer and Zarnowitz, 1969) for single series of forecast is employed. This method essentially regresses the realization on its *ex ante* forecast with the following regression $\sigma_t^2 = \beta_0 + \beta_1 \hat{\sigma}_t^2$, where conditional variance σ_t^2 is replaced by its proxy, and construct the hypothesis on OLS estimates β_0 and β_1, $H_0 : \beta_0 = 0 \cap \beta_1 = 1$ v.s $H_a : \beta_0 \neq 0 \cup \beta_1 \neq 1$. If the forecast is unbiased and explains the volatility assuming the proxy of conditional variance is capturing the underlying volatility, $\beta_0 = 0$ and $\beta_1 = 1$ is expected.

Sometimes pairwise comparison will be needed. Since failure to reject the null hypotheses of the Mincer Zarnowitz regression for the forecasts do not provide evidence on the superiority of one model over another, except that R^2 could be an indicator. Diebold Mariano test (Diebold and Mariano, 1995), however, tries to compare two series of forecasts. It also relies on the proxy of conditional variance. It first computes two series of errors for tow models: $e_{jt} = \hat{\sigma}_{jt}^2 - \sigma_t^2$, where $j \in \{1, 2\}$ and σ_t^2 is the proxy. The difference of these two series of errors, $\{e_{1t} - e_{2t}\}$ is not different from zero if these two methods have the same accuracy in forecasting. Three possible hypotheses tests can be conducted. They share the same null hypothesis that the mean

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[2] An observable variable which is related to the underlying unobservable latent variable.

of the $\{e_{1t} - e_{2t}\}_{t=1}^{T}$ is not different from 0.Three alternative hypotheses includes that the mean is different, greater or less than 0. This testing is related to the predictive accuracy. For example, the mean is statistically greater than 0 is equivalent to less predictive accuracy of the first model.

2.3.7 VaR Backtesting: unconditional coverage, independence, and conditional coverage tests.

Volatility is intrinsically unobservable, and thus forecast must be evaluated with an observable proxy. However, there is no agreed optimal choice for the volatility proxy. Despite being one of the popular choices, the squared returns $\{r_t^2\}_{t=1}^{T}$ series amplifies the outlier and thus forecast error is also amplified. The daily range calculated as the difference between the daily high and daily low is a less noisy choice. When the target is to enhance option hedging efficiency, the option implied volatility could be used as volatility target. When any financial decision is to be made with the forecast, economics loss function which measure the impact of forecast mistake becomes a relevant choice. In this chapter, models and forecasts are also evaluated with proxy-free methods. It evaluates the risk management performance with Value at Risk (VaR) forecast and backtesting.

Based on the conditional distribution forecast[3] and a specified level of confidence α, VaR is calculated after each rolling estimation. VaR is essentially the level of specified α-quantile of the return conditional distribution, i.e. $VaR_\alpha(L) = \inf\{l \in \mathbb{R} : P(L > l) \leq 1 - \alpha\} = \inf\{l \in \mathbb{R} : F_L(l) \geq \alpha\}$ where L is the loss of the portfolio under study. It is widely employed by portfolio managers and institutions for risk management and monitoring purpose. Given the confidence level α for VaR calculation, the long-term frequency of VaR breaks is equal to the per-specified probability α by definition, which means returns may fall below VaR calculated with a probability equal to α. It promises out of T observations, there are actual returns worse than VaR at only $\alpha * T$ times on average. Thus backtesting the VaR forecast can cast light on the volatility modeling.

The violation series constructed from indicator function with *ex ante*

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[3] Here estimating the conditional distribution is to estimate the parameters specifying the distribution.

VaR forecast and *ex post* returns has the following form:

$$I_t = \begin{cases} 1, & \text{if } r_t < -VaR_t^\alpha \text{ (violation)} \\ 0, & \text{if } r_t \geq -VaR_t^\alpha \end{cases},$$

where r_t is the realized return at time t and VaR_t^α is the value at risk forecast for time t given $\mathfrak{F}_{t-1}$, the information set at time $t-1$. This sequence should be by definition unpredictable since the violations only have a pre-specified probability α and are independent.

Kupiec (1995) argues that with correctly specified volatility model and independent VaR hits, T_1 failures out of T observations regardless of order has a probability given by $\alpha^{T_1}(1-\alpha)^{T-T_1}$, where α is the probability of a failure for any one of the T independent trials. The observed fraction of failure in the sequence is given by $\hat{\pi} = \frac{\sum_{i=1}^{T} I_i}{T} = \frac{T_1}{T}$ and the likelihood function yields $L(\hat{\pi}) = (T_1/T)^{T_1}(1-T_1/T)^{(T-T_1)}$. Under $H_0 : \pi = \alpha$ (the VaR is correctly specified) for unconditional coverage test, likelihood function can be expressed as $L(p) = \alpha^{T_1}(1-\alpha)^{T-T_1}$. Therefore, the likelihood ratio test for the null hypothesis that $\pi = \alpha$ has likelihood ratio test with test statistic given by $LR_{\text{uc}} = -2\ln[(1-\alpha)^{T-T_1}\alpha^{T_1}] + 2\ln[(1-\hat{\pi})^{T-T_1}\hat{\pi}^{T_1}]$. It is called PF (proportion of failures) test. Under the null hypothesis, $LR \sim \chi_1^2$, *i.e.* PF test follows a chi-square distribution with 1 degree of freedom.

The above test implicitly assumes the VaR hits are independent. VaR hits, however, are often observed to be clustering, especially when the forecast is made with historical simulation which updates information slowly. Clustering could be a sign of risk model misspecifications since clustering implies that the probability of tomorrow being a hit is higher than the pre-specified probability α if today is a hit. Christoffersen (1998) proposes a method to test the independence against first-order Markov alternative. First-order Markov chain with transition probability matrix $\Pi_1 = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix}$, where $\pi_{ij} = \Pr(I_t = j | I_{t-1} = i)$. The likelihood function $L(\Pi_1) = (1-\pi_{01})^{T_{00}}\pi_{01}^{T_{01}}(1-\pi_{11})^{T_{10}}\pi_{11}^{T_{11}}$, where $T_{ij},\ i,j = 0,1$ is the number of observations with a realization j following a realization i. Maximum likelihood gives matrix of estimated transition probabilities $\hat{\Pi}_1 = \begin{bmatrix} \frac{T_{00}}{T_{00}+T_{01}} & \frac{T_{01}}{T_{00}+T_{01}} \\ \frac{T_{10}}{T_{10}+T_{11}} & \frac{T_{11}}{T_{10}+T_{11}} \end{bmatrix}$ in such an intuitive way. Under the null hypothesis of independent violations $H_0 : \pi_{01} = \pi_{11} = \pi$[4], the transition matrix becomes $\hat{\Pi} = \begin{bmatrix} 1-\hat{\pi} & \hat{\pi} \\ 1-\hat{\pi} & \hat{\pi} \end{bmatrix}$. The likelihood function is $L(\hat{\Pi}) = (1-\hat{\pi})^{T_{00}+T_{10}}\hat{\pi}^{T_{01}+T_{11}} = (1-T_1/T)^{(T-T_1)}(T_1/T)^{T_1}$, the same as the one in alternative hypothesis from the unconditional coverage test. Therefore the likelihood ratio test for independence hypothesis is given as $LR_{\text{ind}} = -2\ln[L(\hat{\Pi})/L(\hat{\Pi}_1)] \sim \chi^2_1$.

In practice, the joint hypothesis of independence and coverage rate are of interest. The joint test combining the test of independence and correct rate is essentially testing for $\pi_{01} = \pi_{11} = \alpha$.[5] It also takes a likelihood ratio form $LR_{\text{cc}} = -2\ln[L(p)/L(\hat{\Pi}_1)] = LR_{\text{ind}} + LR_{\text{uc}} \sim \chi^2_2$.

2.4 Results

2.4.1 Data Description

Commodity trading such as agricultural products has become more complex and influential since Chicago Board of Trade launched future trading in 1884. Price movements have impacts on the future market not only due to the leverage characteristics but also because they reflect information flow related to agricultural production. Four agricultural commodities continuous futures traded on the Chicago Board of Trade (CBOT) are examined: CBOT Corn Futures, #1 (C1), CBOT Rough Rice Futures, #1 (RR1), CBOT Soybean Futures, #1 (S1), CBOT Wheat Futures, #1 (W1). The corn, rice, soybean and wheat commodities continuous futures contracts analyzed are obtained from Quandl via R Application programming interface (API)[6]. It is noted that future contracts have a predetermined life span, and therefore any particular contract expires on the maturity day when the contract is settled. Continuous futures contracts, however, are artificially constructed by chaining different individual contracts on the same product with different expiration dates with particular rolling algorithm to represent future prices in a single series. Daily data spans from 3rd Jan 1994 to 18th Feb 2015. The

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[4] It implies the conditional probabilities of tomorrow being a hit on today being a hit or not are the same

[5] Notice that unconditional coverage test tests for $\pi = p$ and independence test tests for $\pi_{01} = \pi_{11} = \pi$.

[6] Please see `http://cran.r-project.org/web/packages/Quandl/index.html`

original data consist of daily open, high, low, settlement prices, open interest and trading volume. Since settlement price is used to determine profit or loss and margin requirements, it is used for our returns calculation. Daily continuously compounded returns are defined as the natural logarithm of the ratio of settlement price of today to yesterday, *i.e.* $r_t = \ln(\frac{p_t}{p_{t-1}})$.

The descriptive statistics and preliminary test results are given in Table 2.1. Similar to most of the financial data, the means of the four returns are far smaller in magnitude than standard deviations and therefore are not significantly different from zero. However, the Ljung-Box test statistic shows null hypotheses that the 24 lags of auto-correlations are jointly 0 are rejected at less than 1% significance level, suggesting evidence of linear dependence. The four series have kurtosis far larger than 3, suggesting the unconditional distributions of the four series are leptokurtic, or leptokurtotic with sharp peaks and fat tails compared to normal distribution. The signs of skewness are mixed and Jarque Bera test for normality rejects normality for all of the four series at less than 1% significance level. Ljung–Box test statistic for squared returns shows strong dependence in all of the four series. Lagrange multiplier test of Engle (1982) confirms ARCH effect for soybean and wheat at less than 1%, corn at 5% and rice at 10% significance level, which finds evidence on ARCH effect. The contract trading volume along with the price dynamics are shown in Figure 2.1. The price dynamics exhibit similar pattern especially they all increase dramatically around 2007 and 2008 when world food price crisis occurred. Trading activity exhibits tranquil and turbulent periods along the whole span.

2.4.2 Tests for Long Memory

As shown in Table 2.2 and Table 2.3, long memory behavior of the four series is found in squared and absolute returns but not in the return itself by parametric Lo 1991, 's modified R/S test and semi-parametric GPH test. This result suggests the necessity of modeling the long memory behavior in the volatility explicitly.

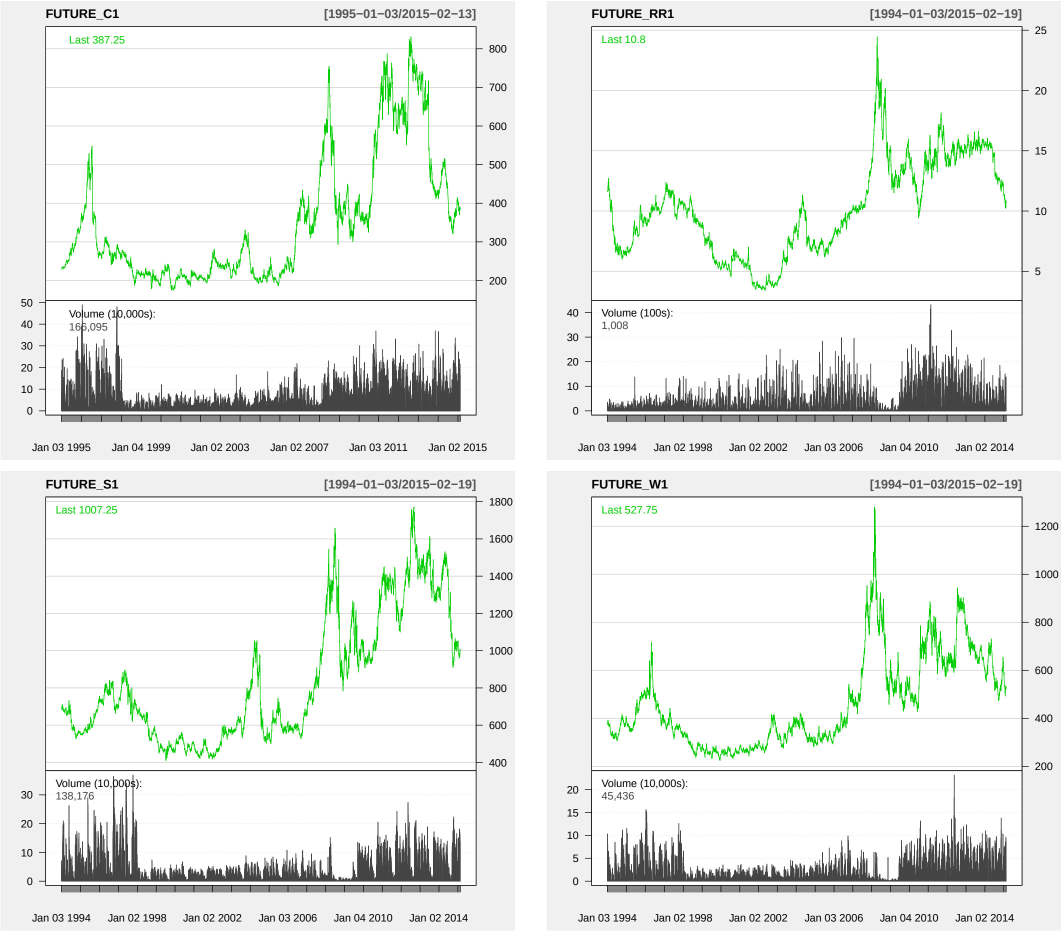

Figure 2.1: Settlement Prices and Trading Volumes for Corn(C1), Rice(RR1), Soybean(S1) and Wheat(W1)

Table 2.1: Descriptive Statistics and Preliminary Test Results for Returns

Return Series	Corn	Rice	Soybean	Wheat
Mean (%)	0.004213	−0.001319	0.02222	0.006535
Minimum (%)	−27.62	−24.45	−23.41	−28.61
Maximum(%)	12.76	28.08	20.32	23.29
Std.Dev (%)	1.836	1.742	1.685	1.999
Skewness	−1.218	0.1073	−1.091	−0.1774
Kurtosis	20.62	24.50781	17.31	12.96
Num. of Obs.	5316	5320	5320	5321
Jarque Bera	95569.9***	133262.9***	67517.9***	37325.3***
$Q(24)$	57.41***	44.12***	66.84***	61.66***
$Q_s(24)$	46.21***	45.09***	964.7***	848.7***
ARCH Test (12)	22.24**	19.07*	688.9***	910.2***

Note: Jarque Bera is the test statistic for Jarque Bera normality test with null hypothesis that sample is from a normal distribution. $Q(24)$ and $Q_s(24)$ are Ljung–Box test statistic with null hypothesis that the 24 lags of auto-correlations are jointly 0 for returns and squared returns, respectively. ARCH test stands for Lagrange multiplier test for null hypothesis that no ARCH effect exists in the series. *, **, *** denote rejection at 10%, 5% and 1% significance level respectively.

Table 2.2: Estimation results from Lo's modified R/S tests for returns, squared returns and absolute returns

	Corn	Rice	Soybean	Wheat
Returns	1.04026	1.52328	1.05564	1.14683
Squared Returns	4.77978***	3.18148***	4.00668***	5.11746***
Absolute Returns	2.62713***	2.22332***	2.46294***	2.36712***

Note: The table of critical values is given in Lo (1991) p.1288.

2.4.3 Estimation

Estimation result of GARCH and Component GARCH for orders from $(1, 1)$, $(1, 2)$, $(2, 1)$, $(2, 2)$ with normal, student, (skewed) general error distribution in total estimated 128 models for 4 series are reported in the Appendix. Residual diagnostics for serial correlation in the standardized residuals and squared standardized residuals pass for all the models but the results are not reported. The optimal orders are selected by BIC with other information criteria provided as well. All of the chosen models pass model checking with standardized residuals and squared of standardized residuals for serial

Table 2.3: Estimation results from GPH tests for returns, squared returns and absolute returns

	Corn	Rice	Soybean	Wheat
Returns	0.06841 (0.4126)	0.1176 (0.1592)	0.02503 (0.7643)	-0.08606 (0.3027)
Squared Returns	0.3039 (0.0003)	0.2737 (0.0010)	0.2881 (0.0006)	0.2227 (0.0077)
Absolute Returns	0.5161 (0.0000)	0.4662 (0.0000)	0.4588 (0.0000)	0.4778 (0.0000)

Note: The null hypothesis is $H_0 : d = 0$ (stationary without long memory) $H_1 : 0 < d < 0.5$ (stationary with long memory). I chose $\alpha = 0.5$ for frequencies $n_f(T)$. The numbers in the parentheses are $p-$ values and asymptotic standard errors for all the estimates are 0.08351.

correlation. In general, optimal orders of lags chosen by four information criteria in most of the GARCH and CGARCH models are $(1, 1)$, $(1, 2)$. BIC is used for the optimal order selection since BIC is consistent by selecting the model with the correct structure with probability one and is used for model comparison across different probability distributions. Except in the case of GARCH specification with normal distribution for wheat for which $(1, 2)$ is picked, all models are selected with $(1, 1)$ by BIC. Within either standard GARCH or component GARCH models with different conditional distributions, BIC favors student distribution over others which suggests fat tail is the most striking stylized fact worth capturing among all the non-normal characteristics in the conditional distribution.

Estimates and their statistical significance across models tend to be robust to the order for lag $(1, 1)$, $(1, 2)$ and $(2, 1)$. When the ε_{t-2}^2 is added into the model in some cases, however, some of the other estimates change to a large extent or become insignificant. For the shape and skew parameters in the student and (skewed) GED distributions, the estimates are all highly significant and robust across different orders within the same model and across both standard GARCH and component GARCH model. This finding again documents evidence for the non-normal characteristics for the conditional distribution such as skewness and heavy tails. One interesting finding regarding the skewness as measured by the inverse scale factor is that almost all estimates for skew are significantly larger than 1 for corn and wheat, insignificant for rice and significantly smaller than 1 for soybean both in standard GARCH and component GARCH model. This result suggests more extremely positive shocks for corn and wheat returns but more extremely negative shocks for soybean.

The estimates of the short term components parameters are highly significant except in the case of short term component with student distribution for rice, and short term component with sged distribution for soybean. All of the estimates for long term component parameters are significant at 0.1% and close to unity with the range from 0.981 to 0.99909. It suggests the component structure in the volatility. Focusing on the component GARCH model with optimal conditional distributions selected by BIC, the long run component estimates suggests half life ranging from 50 to 90 trading days, which is equivalent to 2 to 4 months. On the contrary, the standard GARCH model counterparts suggest shorter periods from 40 to 60 trading days.

Diebold-Mariano test for predictive accuracy is employed on the out of sample rolling estimation with one day ahead forecast. In the Table in Apendix, DM Statistic shows the test statistic, and the third to fifth columns show the p values for three hypotheses with the same null hypothesis but different alternative hypotheses. Null hypothesis is that standard GARCH and component GARCH have the same accuracy and different alternative hypotheses are two methods have different predictive accuracy, component GARCH is more accurate and component GARCH is less precise. The Diebold-Mariano test compares the result the predictive accuracy of models with the same order and same distributional assumption and find for corn, soybean and wheat. There is strong evidence for the superiority of the component GARCH model. However, in the case of rice return, predictive accuracy superiority only exists for models with normal distribution and it is inconclusive for model with other distributions.

Diebold-Mariano test compares the forecast error, but the result could be sensitive to the choice of the volatility proxy. Thus, in each of the rolling estimations, the conditional density of the return of the next period is calculated with the estimates of the GARCH model and conditional distribution. The ex-ante VaR_{t+1}^{α} is calculated and compared with the ex-ante realization of return r_{t+1} to arrive at a violation series. The violation series is backtested and the result is reported in Table 2.4, 2.5, 2.6 and 2.7. Both results with

$\alpha = 0.01$ and $\alpha = 0.05$ are reported. The quantiles chosen here have nothing to do with conventional level of statistical significance but the adequacy of capturing the tail behavior of the density forecast. The last 1500 returns are kept for out of the sample forecast and expected VaR exceedances of are 15 and 75 for $\alpha = 1\%$ and $\alpha = 5$ respectively. For the unconditional test (Kupiec, 1995), the closer total actual VaR violations is to the expected ones, the better the model is capturing the lower α quantile. On one hand, if the ex-post VaR violations are statistically more than the expected occurrences, the actual left tail of the underlying conditional distribution will have fatter tail than the one modeled. On the other hand, the model can be overestimating the variance as well as the VaR forecast. In our estimation, both unconditional coverage test (Kupiec, 1995) and conditional coverage test (Christoffersen, 1998) are more likely to reject the null hypothesis of correct unconditional coverage with the coverage ratio $\alpha = 1\%$ than with coverage ratio $\alpha = 5\%$. This result suggests the estimated models is inadequate for capturing the most extreme events compared to the less extreme events. Violation clustering in the $\alpha = 1\%$ tail also suggests the potential failure of both GARCH models to update the one in a hundred worst return for the volatility. For the conditional coverage test (Christoffersen, 1998), not only the total actual VaR violations but also the order of the violations matters. Among all the distribution, the VaR forecast seems to perform best with the student distribution, which is consistent with the result of the information criteria, although both skewness and shape parameters of sged are also found to be highly significant. It suggests the estimation of the additional parameters may also increase the estimation error and subsequent inaccuracy in out of sample forecast despite the existence of the skewness in the conditional distribution. When comparing the VaR backtesting result for the two GARCH models, one should find out the component GARCH model performs at least as well as the standard GARCH model with the same conditional distribution.

2.5 Conclusion

This chapter examines the long run dependence in return volatility of the four agricultural commodity futures, namely, corn, rice, soybean, and wheat

Table 2.4: VaR backtesting result for corn

Model	Standard GARCH / Component GARCH							
Conditional Dist.	norm		std		ged		sged	
$\alpha = 1\%$								
Actual VaR Exceed	28	27	23	20	23	23	25	24
LR.uc Statistic	9.067	7.838	3.706	1.524	3.706	3.706	5.609	4.615
LR.uc p-value	0.3%	0.5%	5.4%	21.7%	5.4%	5.4%	1.8%	3.2%
LR.cc Statistic	9.426	8.272	4.532	2.756	4.532	4.532	6.22	5.329
LR.cc p-value	0.9%	1.6%	10.4%	25.2%	10.4%	10.4%	4.5%	7%
$\alpha = 5\%$								
Actual VaR Exceed	57	62	75	74	62	66	69	68
LR.uc Statistic	4.941	2.514	0	0.014	2.514	1.183	0.519	0.709
LR.uc p-value	2.6%	11.3%	100%	90.5%	11.3%	27.7%	47.1%	40%
LR.cc Statistic	5.252	2.66	0.026	0.061	3.323	1.19	0.764	1.014
LR.cc p-value	7.2%	26.5%	98.7%	97%	19%	55.2%	68.2%	60.2%

Note: With sample size 1500, expected exceedences are 15 and 75 for $\alpha = 1\%$ and $\alpha = 5$ respectively. LR.uc stands for likelihood ratio test for unconditional coverage test (Kupiec, 1995). LR.uc stands for likelihood ratio test for conditional coverage test Christoffersen (1998).

Table 2.5: VaR backtesting result for rice

Model	Standard GARCH / Component GARCH							
Conditional Dist.	norm		std		ged		sged	
$\alpha = 1\%$								
Actual VaR Exceed	7	7	12	12	4	6	6	6
LR.uc Statistic	5.373	5.373	0.651	0.651	11.507	7.059	7.059	7.059
LR.uc p-value	2%	2%	42%	42%	0.1%	0.8%	0.8%	0.8%
LR.cc Statistic	6.745	5.773	0.713	0.713	12.743	8.193	10.13	9.52
LR.cc p-value	3.43%	5.58%	70.0%	70.0%	0.17%	1.66%	0.63%	0.85%
$\alpha = 5\%$								
Actual VaR Exceed	53	55	67	71	57	62	60	62
LR.uc Statistic	7.535	6.162	0.93	0.228	4.941	2.514	3.841	2.514
LR.uc p-value	0.6%	1.3%	33.5%	63.3%	2.6%	11.3%	6.6%	11.3%
LR.cc Statistic	9.532	7.825	4.33	3.487	6.304	6.257	5.759	6.257
LR.cc p-value	0.9%	2%	11.47%	17.49%	4.3%	4.4%	5.6%	4.4%

Note: With sample size 1500, expected exceedences are 15 and 75 for $\alpha = 1\%$ and $\alpha = 5$ respectively. LR.uc stands for likelihood ratio test for unconditional coverage test (Kupiec, 1995). LR.uc stands for likelihood ratio test for conditional coverage test Christoffersen (1998).

Table 2.6: VaR backtesting result for soybean

Model	Standard GARCH / Component GARCH							
Conditional Dist.	norm		std		ged		sged	
$\alpha = 1\%$								
Actual VaR Exceed	31	30	23	21	22	22	21	20
LR.uc Statistic	13.181	11.741	3.706	2.156	2.885	2.885	2.156	1.524
LR.uc p-value	0%	0.1%	5.4%	14.2%	8.9%	8.9%	14.2%	21.7%
LR.cc Statistic	13.361	11.973	4.532	3.241	3.834	3.834	3.241	2.756
LR.cc p-value	0.1%	0.3%	10.4%	19.8%	14.7%	14.7%	19.8%	25.2%
$\alpha = 5\%$								
Actual VaR Exceed	79	76	82	85	79	78	73	71
LR.uc Statistic	0.221	0.014	0.668	1.348	0.221	0.125	0.057	0.228
LR.uc p-value	63.8%	90.6%	41.4%	24.6%	63.8%	72.4%	81.2%	63.3%
LR.cc Statistic	3.409	0.363	5.991	3.358	3.409	1.039	4.74	1.002
LR.cc p-value	18.2%	83.4%	9.4%	18.7%	18.2%	59.5%	9.3%	60.6%

Note: With sample size 1500, expected exceedences are 15 and 75 for $\alpha = 1\%$ and $\alpha = 5$ respectively. LR.uc stands for likelihood ratio test for unconditional coverage test (Kupiec, 1995). LR.uc stands for likelihood ratio test for conditional coverage test Christoffersen (1998).

Table 2.7: VaR backtesting result for wheat

Model	Standard GARCH / Component GARCH							
Conditional Dist.	norm		std		ged		sged	
				$\alpha = 1\%$				
Actual VaR Exceed	17	15	14	14	13	13	18	15
LR.uc Statistic	0.258	0	0.069	0.069	0.282	0.282	0.57	0
LR.uc p-value	61.1%	100%	79.3%	79.3%	59.5%	59.5%	45%	100%
LR.cc Statistic	0.367	0.014	0.175	0.134	0.349	0.467	0.671	0.013
LR.cc p-value	83.2%	99.3%	91.6%	93.5%	83.9%	79.2%	71.5%	99.3%
				$\alpha = 5\%$				
Actual VaR Exceed	75	71	76	75	72	71	81	79
LR.uc Statistic	0	0.228	0.014	0	0.128	0.228	0.493	0.221
LR.uc p-value	100%	63.3%	90.6%	100%	72.1%	63.3%	48.3%	63.8%
LR.cc Statistic	0.018	0.273	0.02	0.42	0.217	0.355	0.588	0.398
LR.cc p-value	99.1%	87.2%	99%	81%	89.7%	83.8%	74.5%	82%

Note: With sample size 1500, expected exceedences are 15 and 75 for $\alpha = 1\%$ and $\alpha = 5$ respectively. LR.uc stands for likelihood ratio test for unconditional coverage test (Kupiec, 1995). LR.uc stands for likelihood ratio test for conditional coverage test Christoffersen (1998).

with daily returns from 3rd Jan 1994 to 18th Feb 2015. It confirms the existence of the long run dependency with two tests. The return volatility is later modeled by standard GARCH model and component GARCH model with normal, student, (skewed) generalized error distributions and different lag specifications. The estimated models confirm the long run and short run component structure with component GARCH model in most of the cases. In addition to the heavy-tailness, skewness of the conditional distribution is also found with strong evidence. The estimated model optimal lag and conditional distribution were then rolled over for out of sample one day ahead conditional variance forecast and VaR forecast. The out of sample forecast evaluation with Diebold-Mariano test suggests the superiority of the component GARCH over the standard GARCH model. The VaR forecast is backtested with unconditional coverage and conditional coverage test and the results again favor the component GARCH over standard GARCH model for risk management purposes. The existing literature does not pay much attention to the long memory volatility in agricultural commodity given the importance of economic decision related to volatility such as risk management, portfolio optimization, option pricing, etc and the devastating consequences their failure would bring. This chapter contributes by documenting the empirical evidence on the existence of volatility persistence and the superiority of component GARCH model over standard GARCH model in modeling the conditional volatility process as evidenced by out of sample forecast valuation as well as VaR backtesting.

Chapter 3

Essay Two: Asymmetric Price Transmission in Global Energy Grain Nexus

3.1 Introduction

Since the beginning of the 21^{st} century, the global agricultural commodity price has increased dramatically. Especially the global food crises during 2007 to 2008 led to political and economic instability as well as social unrest. It has attracted attention from policy makers, international investors, as well as academia. Food prices are of welfare implication especially for those countries relying heavily on food import from the policy perspective. Agricultural commodity is also one of the main asset classes and industrial inputs when it comes to asset allocation for asset managers, investment for investors as well as risk management for industrial producers. Researchers argue that energy price is one of the main driver for rocking agricultural commodity prices through three channels. The first channel is through agricultural production cost for input such as diesel, fertilizers, and pesticides. Historically agricultural sector has been energy intensive. Without considering the energy stored during the process of photosynthesis, planting, harvest and transportation for agricultural industrial are energy demanding especially in industrialized countries. Second, the recent rapid development in biofuel has strengthened the energy-agricultural linkage, *i.e.*, the food v.s. fuel trade-off. Biomass such as corn and sugarcane as input can be converted into ethanol and bio-diesel, which are substitutes for fossil fuels. Renewable Fuels Association (RFA, 2014) estimates the global fuel ethanol production to be 24.5 billion of gallons based on public and private sources. It is also reported biodiesel production in European Union adds up to 10 million tons (EBB, 2013) and global biodiesel production estimate is 5.6 billion of gallons Brown (2012). Economic theory suggests fossil fuel prices rise could boost the price of the biofuel as substitute good and hence increase the value of the marginal product of agricultural commodity as well as its demand. It in turn squeezes out or crowds out the agricultural commodity for food consumption. The above two channels focus on the direct effect of energy on agricultural commodity while the third link involves exchange rate in an indirect manner. Most oil contracts traded globally are denominated in U.S.D, and therefore the appreciation (or depreciation) of the U.S.D against local currency will result in the increase (or decrease) in the local prices of the oil related inputs. Hence it affects the local price of agricultural products.

In the next section, related literature on price transmission and energy-agricultural linkage modeling is reviewed. In section 3, methodology and models applied in this chapter are discussed. It is followed by the estimation result which shows there is evidence of non-linearity in price transmission between energy-agricultural indices. The chapter ends with the conclusion and the potential.

3.2 Literature Review: Mixed Findings in the Linkage

There are several strands of literature related to the energy-agricultural linkage with the majority focusing on empirical evidence. Starting from the theoretical models studying the adjustment channels, Gardner (2007) illustrates how under different subsidy schemes, corn growers would prefer the government's subsidy dollar spent directly on corn subsidies or a subsidy on ethanol made from corn with a vertical market model involving ethanol, byproduct, and corn production. De Gorter and Just (2008) relate price of ethanol to corn and oil prices through two key policies - consumer fuel tax with differential biofuel tax exemption and biofuel mandates. This model is extended in De Gorter and Just (2009) to consider the interaction effect of tax credit for biofuel consumption with price contingent production subsidies as well as its welfare implication. All these models only incorporate the channel of demand for agricultural commodity as input biofuel production but fail to consider the indirect mechanism of fossil fuel as an input in agricultural commodity production. Besides, theses models focus on effect on biomass commodity but ignore the possibility of affecting commodity not used in biofuel production. These two shortcomings are resolved in a vertically integrated theoretical model developed in Ciaian and Kancs (2011b) and Ciaian and Kancs (2011a). In these two papers, both biomass used for biofuel production and food not suitable for biofuel production are included in the model to illustrate the interaction effect among commodity market. Fossil fuel as indispensable input for agricultural commodity is also considered.

Empirical analysis of the existing literature regarding biofuel related commodity transmission concentrates on both price level and volatility level. The family of conditional volatility models stimulated by autoregressive conditional heteroskedasticity (ARCH) (Engle, 1982) and its subsequent generalized autoregressive conditional heteroskedasticity (GARCH) (Bollerslev, 1986) has been the one of the workhorses for time varying and clustering volatility modeling. Multivariate GRACH model serves as an example in the existing literature to study the volatility dynamics interaction and spillover (Serra and Gil 2012; Serra, Zilberman, and Gil 2011; Trujillo-Barrera, Mallory, and Garcia 2012; Wu, Guan, and Myers 2011; Zhang, Lohr, Escalante, and Wetzstein 2008,0). Similarly, since the seminal work of Nobel laureate Engle and Granger (1987b), vector error correction model (VECM) and its extension have been utilized to study the long run equilibrium between nonstationary variables and their disequilibrium adjustment process. This chapter focuses on the price dynamics interaction. The existing literature mainly utilizes VECM and the finding regarding the price interaction is mixed. Most authors find evidence on biofuel or energy price affecting feed-stock prices in the long run with local or international data ranging from quarterly data to daily data (Balcombe and Rapsomanikis, 2008; Busse et al., 2012; Campiche et al., 2007; Ciaian and Kancs, 2011a,1, among others) while other do not (Hassouneh et al., 2012; Mallory et al., 2012; Qiu et al., 2012; Yu et al., 2006;

Zhang and Reed, 2008). As pointed out by Enders and Granger (1998), tests for unit roots and cointegration have low power to detect unit roots or cointegration in the presence of asymmetric adjustment. It is possible that the failure of some of the existing literature to detect cointegration is due to the failure to take care of the asymmetry. Therefore this chapter investigates the possible nonlinearity by applying nonlinear cointegration methods with ECM proposed by Sun (2011).

Literature on nonlinear time series models concerning adjustment mechanism has grown in recent years. Studies regarding the key macroeconomic variables such as gross real product, unemployment and industrial production have shown evidence on asymmetric adjustment. Extension to multivariate models on asymmetric adjustment have also witnessed its rapid growth in examining relevant macroeconomic variables and financial variable such as production, inventory, and inters rates. For example, Siklos and Granger (1997) find the time varying strength in the interest rate parity. Enders and Granger (1998) and Enders and Siklos (2001) examine the long term and short term interest rate with asymmetric adjustment. One concept closely related to nonlinear cointegration is asymmetric price transmission. It is referred to a phenomenon that price series responds systematically differently to previous positive and negative price changes. It is observed that in many markets output prices respond asymmetrically to input price changes, and this may point to a gap in economics theory. Asymmetric price transmission (APT) also has policy implication in term of welfare distribution between producers and costumers. Meyer and Cramon-Taubadel (2004) and Frey and Manera (2007) serve as two survey papers on asymmetric price transmission. In Meyer and Cramon-Taubadel (2004), the authors classify types of asymmetric price transmission according to three criteria, namely, whether the speed or magnitude of price transmission is asymmetric, whether output prices respond more fully or rapidly to an increase in input prices than to a decrease (positive or negative), and whether it affects prices in different level of the market chain or at different areas (vertical or spatial). It also reviews the causes of asymmetric price transmission proposed in the literature such as market power, adjustment and menu cost, price support and *etc.* Frey and Manera (2007) survey the nonlinear econometric models that could be applied to study asymmetric price transmission.

The authors classify the models into four types, namely the autoregressive distributed lag (ARDL) model, the partial adjustment model (PAM), the error (or equilibrium) correction model (ECM), the regime switching model (RSM) with their multivariate extensions. In this chapter, linear and nonlinear cointegration and error correction model are employed only to study the asymmetry on the speed of price transmission, but not the magnitude, since APT with regard to magnitude implies permanent shocks and effect, which is driving the variables apart in the long run and thus render the variables in the system unable to be cointegrated.

3.3 Methodology

Cointegration was proposed in the beginning of 1980's by Engle and Granger (1987b) and has been applied to study the long run relationship between economics variables. Its recent development can be found in Johansen (2009). In this chapter, both of the Johansen and Engle-Granger two-step approaches are utilized to model cointegration and they both assume linear and symmetric relation between variables. However, in recent year, it has been documented that the relationship between commodities exhibits asymmetry. Thus threshold cointegration and its asymmetric error correction model are also employed to study global energy grain nexus.

3.3.1 Engle-Granger two-stage approach

Engle and Granger (1987b) propose an two-step approach to estimate long run equilibrium based on symmetric error process as follow.

$$g_t = \beta_0 + \beta_1 n_t + \epsilon_t \tag{9}$$

$$\Delta\hat{\epsilon}_t = \rho\hat{\epsilon}_{t-1} + \sum_{i=1}^{p} \phi_i \Delta\hat{\epsilon}_{t-i} + \varepsilon_t \tag{10}$$

where β_o, β_1, ρ, and ϕ_i are coefficients, ϵ_t is the error term, $\hat{\epsilon}_t$ is the estimated residuals from the Eq.(9) by OLS, Δ indicates the difference operator, ε_t is a white noise error term, and p is the number of the lags. In the first step, global grain price index g_t and is regressed on global energy price index n_t since energy price is assumed to be driving force of the dynamics as standard practice and finding in the literature. Although this method forces the researcher to treat the two variables in the system asymmetrically, similar result for this approach and the following methods is found when these two variables are treated the other way around.

Suppose two variables g_t and n_t are both integrated of order one, *i.e.* $I(1)$. The first step is to run the regression in Eq.(9). If the two variable g_t and n_t are indeed co-integrated, denoted as $CI(1,1)$, the residuals $\hat{\epsilon}_t$ will be stationary and the OLS estimate of the weight (the long-run parameter estimate) $\hat{\beta}_1$ from the first step regression will be super-consistent, which means they converge to the population value faster than they do in OLS models with stationary variables[1]. In the second step, the stationarity of the residual series $\hat{\epsilon}_t$ is tested by performing Augmented Dickey–Fuller test with the auto-regression in Eq.(10). To correct for the serial correlation in the regression residuals $\hat{\varepsilon}_t$, lagged values $\Delta\hat{\varepsilon}_{t-i}$ were added and the number of lag could be selected by information criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), or diagnostic tests such as Ljung–Box Q test. The failure to reject the $H_0 : \rho = 0$ (the null hypothesis of non-stationarity) can confirm the unit root in the residuals which in turn excludes the possibility of cointegration of g_t and n_t. Otherwise, the rejection of the null hypothesis of unit root in the residuals will imply stationarity of the residual sequence $\hat{\epsilon}_t$ and cointegration of g_t and n_t. However, one should note that OLS fits the model by minimizing the sum of squared residuals. Therefore without the prior information regarding the true β_0 and β_1 as in the case where long run relationship in Eq.(9) is estimated but not predetermined as suggested by theory, the estimated residuals will be biased toward finding a stationary error process. Hence, the ADF and PP unit root tests on the Eq.(10) do not follow the usual Dickey-Fuller distributions under the null hypothesis of no-cointegration but instead the PO distributions (Phillips and Ouliaris, 1990).

As guaranteed by Granger representation theorem, the evidence on cointegration ($\rho \neq 0$) could be followed by error correction model which takes out the 1 lagged residual $\hat{\epsilon}_{t-1}$ as deviation from the long run equilibrium relationship and puts it as error correction term into the error-correcting

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[1] If $\hat{\phi}$ is super-consistent, $\hat{\phi} \xrightarrow{p} \phi$ at at rate T instead of the usual rate $T^{1/2}$

model:

$$\Delta g_t = \alpha_1 + \alpha_g \hat{\epsilon}_{t-1} + \sum_{i=1} \alpha_{11}(i) \Delta g_{t-i} + \sum_{i=1} \alpha_{12}(i) \Delta n_{t-i} + u_{gt} \tag{11}$$

$$\Delta n_t = \alpha_2 + \alpha_n \hat{\epsilon}_{t-1} + \sum_{i=1} \alpha_{21}(i) \Delta g_{t-i} + \sum_{i=1} \alpha_{22}(i) \Delta n_{t-i} + u_{nt} \tag{12}$$

3.3.2 Johasen's method

Although the Engle and Granger (1987b) procedure is easily implemented, it requires an asymmetric and an choice of left-hand side and right-hand side variables and two-step estimation may carry on error from the first to the second. The Granger representation theorem (Engle and Granger, 1987b) establishes the equivalence for cointegration and error correction model and Johansen (1988) establishes cointegration and error correction models in a vector autoregression framework. Specifically, Johansen (1988) generalizes the Dickey–Fuller test to multivariate case and treat all the variables in the potential cointegration system symmetrically by starting from the so-called levels vector autoregressive with k lags and rearranging it into a vector autoregressive model in the differenced variable as follows:

$$X_t = \mu + \Phi D_t + \Pi_1 X_{t-1} + \cdots + \Pi_k X_{t-k} + \xi_t \tag{13}$$

$$\Delta X_t = \mu + \Phi D_t + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-k} + \xi_t \text{ or,} \tag{14}$$

$$\Delta X_t = \mu + \Phi D_t + \sum_{i=1}^{k-1} \Gamma'_i \Delta X_{t-i} + \Pi X_{t-1} + \xi_t \tag{15}$$

where X_t are vector of variables of interests at time t, k is the number of lag, Π_i are coefficient matrices for level VAR, ξ_t is an unobservable zero mean white noise vector process, Δ indicates the differencing operator, and I is the identity matrix, the $\Gamma_i = \sum_{j=1}^{i} \Pi_j - I$ represent cumulative long-run impacts in Eq.(14); $\Gamma'_i = -\sum_{j=i+1}^{k} \Pi_j$ measures transitory effects and are called the short-run impact matrices in Eq.(15) $\Pi = \sum_{i=1}^{k} \Pi_i - I$ is the same in the two specifications. The approach of Johansen (1988) examines cointegration relationship by constructing likelihood ratio tests for the rank of Π to determine the number of cointegrating vectors. It is evident from Eq.(13) that unit roots in $VAR(k)$ process require Π to be a singular matrix and therefore has reduced rank i.e., $\text{rank}(\Pi) = r < n$. There are two cases to consider: *i*) $\text{rank}(\Pi) = 0$ implies that $\Pi = \mathbf{0}$ and X_t is $I(1)$ and not cointegrated; *ii*) $0 < \text{rank}(\Pi) = r < n$ implies X_t is $I(1)$ with r linearly independent cointegrating vectors and common stochastic trends in the system. In practice, with only the estimated $\hat{\Pi}$ the characteristic roots or eigenvalues can be calculated and ordered in such a way that $\lambda_1 > \lambda_2 > \cdots > \lambda_n$. There are two likelihood ratio tests with the same null hypothesis but different alternative hypotheses. Johansen's LR statistic tests the nested hypotheses $H_0(r) : r = r_0$ v.s. $H_a(r_0) : r > r_0$ with LR statistic, called the trace statistic given by $\lambda_{\text{trace}}(r_0) = -T \sum_{i=r_o+1}^{n} \ln(1-\hat{\lambda}_i)$. Johansen proposes a sequential bottom-up procedure to consistently determines the number of cointegrating vectors by first testing $H_0(r = 0)$ against $H_a(r > 0)$ and, if it is rejected, move on to $H_0(r = 1)$ against $H_a(r > 1)$. This procedure carries on until the failure to reject the null hypothesis and one can conclude that the number of cointegrating vectors is equal to the value under the null one fails to reject. The maximum eigenvalue statistic for the hypotheses $H_0(r) : r = r_0$ v.s. $H_a(r_0) : r = r_0 + 1$ is given by $\lambda_{\max}(r_0) = -T \ln(1 - \hat{\lambda}_{r_0+1})$. The basic idea behind these two tests is that if $\text{rank}(\Pi) = r_0$, then $\lambda_{r_0+1}, \cdots, \lambda_n$ will be close to zero and $\lambda_{\text{trace}}(r_0)$ and $\lambda_{\max}(r_0)$ will therefore be small. Otherwise, if $\text{rank}(\Pi) > r_0$, $\lambda_{\text{trace}}(r_0)$ and $\lambda_{\max}(r_0)$ will be large. Both LR statistic do not follow chi-square distribution but are tabulated in Osterwald-Lenum (1992).

3.3.3 Threshold Cointegration

Traditionally, cointegration tests such as Engle and Granger (1987b) and Johansen (1988) assume linear adjustment in the cointegration. In other words, those literature on convergence to the long-run equilibrium does not distinguish between adjustments from below the threshold, known as spread widening, and adjustment from above the threshold, noted as spread narrowing (Chang, Chen, Hammoudeh, and McAleer, 2012a). Threshold autoregressive (TAR) models developed by Tong (1983) and Tong (1990) break the autoregressive terms into different decaying speeds based on the state variable or the regime. Similarly, momentum threshold autoregression specification proposed in Enders and Granger (1998) modifies the standard

Dickey-Fuller tests by incorporating asymmetric adjustment. It allows the variable of interest to have different decaying amounts in the autoregressive terms based on whether it is increasing or decreasing. It has the null hypothesis of a unit root against the alternative of stationarity with asymmetric adjustment. Enders and Siklos (2001) adopt the specification of Enders and Granger (1998) to examine cointegration residuals dynamics from the first step regression. The first step in Enders and Siklos (2001) is to run a regression in Eq.(9), same as the first step in Engle and Granger (1987b), followed by an extension of the second step shown below:

$$\Delta\hat{\epsilon}_t = \rho^+ I_t \hat{\epsilon}_{t-1} + \rho^-(1 - I_t)\hat{\epsilon}_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta\hat{\epsilon}_{t-i} + \varepsilon_t \tag{16}$$

$$I_t = \begin{cases} 1 & \text{if } \hat{\epsilon}_{t-1} \geq \tau \\ 0 & \text{if } \hat{\epsilon}_{t-1} < \tau \end{cases} \quad \text{or} \tag{17}$$

$$I_t = \begin{cases} 1 & \text{if } \Delta\hat{\epsilon}_{t-1} \geq \tau \\ 0 & \text{if } \Delta\hat{\epsilon}_{t-1} < \tau \end{cases} \tag{18}$$

where I_t is indicator function, ρ^+, ρ^-, φ_i, are coefficients, and τ is the threshold value, $\varepsilon_t \sim IID(0, \sigma^2)$ and p is the number of lags specified to correct for the serial correlation in the residuals and it can be selected by information criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), or diagnostic tests such as Ljung–Box Q test. Due to the unknown nature of the nonlinearity, the adjustment can either depend on the level of the lagged residuals or the changes in the residuals, indicator function at time t concerning the threshold value could be specified on the residuals at the previous period or the changes in the residuals at the previous period expressed in Eq.(17) and Eq.(18). They along with Eq.(16) are referred to as threshold autoregression cointegration model and the Momentum Threshold Autoregression cointegration model respectively. M-TAR cointegration model becomes especially relevant specification when the series exhibits more momentum in one direction than the other.

The threshold value τ could be either specified or estimated. However, in practice, researchers do not have the luxury of knowing the true value of τ even if he or she knows the true data generating process is TAR or

M-TAR. Tong (1983) and Tong (1990) suggest a non-parametric lag regression procedure to estimate the values of the thresholds. Ideally, one should endogenously estimate τ along with other parameters in the model with non-linear least squares (NLS) estimation procedure, but the discontinuity in the thresholds of the underlying functional relationship between the variables renders it infeasible. Fortunately, Chan (1993) shows a procedure to obtain a super-consistent estimate of the threshold value. First of all, if a threshold value makes sense, it must cross the whole series of data, i.e. $\tau \in (\min_{0\leq t\leq T}\{\hat{\epsilon}_t\}, \max_{0\leq t\leq T}\{\hat{\epsilon}_t\})$ for TAR and $\tau \in (\min_{0\leq t\leq T}\{\Delta\hat{\epsilon}_t\}, \max_{0\leq t\leq T}\{\Delta\hat{\epsilon}_t\})$ for M-TAR, otherwise, $I_t = 1$ or $I_t = 0$ for all t. In empirical practice the highest 15% and lowest 15% observations of the series are excluded from the grid search procedure for the adequacy of observations lying on both sides of the threshold. Each data point of remaining middle 70% of the observation will be chosen as the threshold value one by one and researcher should estimate the model accordingly. Finally, the model with the smallest residual sum of squares in Eq.(16) will contain the consistent estimate of the threshold i.e., $\hat{\tau} = \arg\min \sum \hat{\varepsilon}_t^2$. The threshold value in M-TAR could explain positive transaction cost or adjustment cost. It is also shown in the literature M-TAR model with consistently estimated threshold value fit the data better than TAR, M-TAR with $\tau = 0$ according to AIC (see Balke and Fomby, 1997; Chan, 1993; Enders and Siklos, 2001). Therefore, TAR and M-TAR model are estimated with consistent threshold and threshold value $\tau = 0$ and compare the interpretation.

In Eq.(10), the existence of cointegration is tested with null hypothesis $H_0 : \rho = 0$, and one should notice in Eq.(16), $\rho^+ = \rho^- = 0$ incorporates Engle-Granger test as a special case. Tong (1983) and Tong (1990) showed least square estimate of ρ^+ and ρ^- have bi-variate normal distribution. The necessary and sufficient conditions for the stationarity of $\{\hat{\epsilon}_t\}$ is $\rho^+ < 0$, $\rho^- < 0$ and $(\rho^+ + 1)(\rho^- + 1) < 1$ (Petruccelli and Woolford, 1984). Cointegration is established by rejecting joint hypothesis of no cointegration $H_0 : \rho^+ = \rho^- = 0$ against an nonlinear cointegration alternative hypothesis. However, the classic F-statistic is not applicable to the F-test for this joint hypothesis but one need to use critical values for Φ and Φ^* in Enders and Siklos (2001) for model with $\tau = 0$ and consistently estimated τ. Enders and Siklos (2001) conduct two Monte Carlo experiments that can be used to test the null hypothesis of no cointegration against the alternative of either TAR cointegration or MTAR cointegration with threshold adjustment. If the null hypothesis of no cointegration is rejected, one can try to examine whether the cointegration residuals dynamics exhibits nonlinearity. To test for symmetric versus asymmetric adjustment requires performing F-test on null hypothesis $H_0 : \rho^+ = \rho^-$ using a standard F-distribution.

3.3.4 Bivariate Error Correction Model with TAR or MTAR Cointegration

When the threshold cointegration is found present, the error correction terms could be modified to include asymmetry. Asymmetry is introduced into the adjustment process by modifying the error correction terms as well as the adjustment coefficients in the error-correcting model as developed in Sun (2011)[2] as follows:

$$
\begin{aligned}
\Delta g_t &= \theta_g + \delta_g^+ E_{t-1}^+ + \delta_g^- E_{t-1}^- + \sum_{i=1}^{J} \alpha_{gi}^+ \Delta g_{t-i}^+ + \sum_{i=1}^{J} \alpha_{gi}^- \Delta g_{t-i}^- \\
&\quad + \sum_{i=1}^{J} \beta_{gi}^+ \Delta n_{t-i}^+ + \sum_{i=1}^{J} \beta_{gi}^- \Delta n_{t-i}^- + \vartheta_{gt} \\
\Delta n_t &= \theta_n + \delta_n^+ E_{t-1}^+ + \delta_n^- E_{t-1}^- + \sum_{i=1}^{J} \alpha_{ni}^+ \Delta g_{t-i}^+ + \sum_{i=1}^{J} \alpha_{ni}^- \Delta g_{t-i}^- \\
&\quad + \sum_{i=1}^{J} \beta_{ni}^+ \Delta n_{t-i}^+ + \sum_{i=1}^{J} \beta_{ni}^- \Delta n_{t-i}^- + \vartheta_{nt}
\end{aligned}
$$

where θ's, δ's, α's, and β's, are coefficients, Δg_t and Δn_t are log value of grain and energy indices in first difference. $E_{t-1}^+ = I_t \hat{\epsilon}_{t-1}$, $E_{t-1}^- = (1-I_t)\hat{\epsilon}_{t-1}$, where $\hat{\epsilon}_{t-1}$ is the residual series from Eq.(16) and I_t is the indicator function defined in Eq.(17) or Eq.(18) for specifications corresponding to TAR and MTAR. With Δg_{t-i}^+, Δg_{t-i}^-, Δn_{t-i}^+ and Δn_{t-i}^-, the superscripts "+" and "−" split the changes of the variables into positive and negative change parts. For instance, $\Delta g_{t-i}^+ = \begin{cases} \Delta g_{t-i} = g_{t-i} - g_{t-i-1} & \text{if } g_{t-i} - g_{t-i-1} \geq 0 \\ 0 & \text{if } g_{t-i} - g_{t-i-1} < 0 \end{cases}$. J lags are added to the model to correct for the serial correlation of the error term

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[2] Dr. Sun also develops a packages "apt' (Sun, 2014) in R (R Core Team, 2015)

ϑ_{it} for $i = g, e$. The validity of the error correction model can be examined by preliminarily checking the significance and signs of the estimates for the error correction terms given the long run equilibrium specified in Eq.(9). As discussed in Frey and Manera (2007), several kinds of hypotheses could be performed on the parameters such as Granger causality test, distributed asymmetry test, cumulative asymmetry test and equilibrium adjustment path asymmetry test.

3.4 Empirical results

3.4.1 Data Description and Unit Root Test

The World Bank monitors major global commodity markets, collects and publishes monthly commodities for over 70 prices series and indices as presented in the World Bank Commodity Price Data, also known as Pink Sheet from 1960 to present on a monthly basis[3]. This chapter chooses energy index and grain index, denoted as $\{E_t\}_{t=1}^{T}$ and $\{G_t\}_{t=1}^{T}$. The former is a Laspeyres index with fixed weights based on 2002-2004 average developing countries export values, for coal, crude oil and natural gas with value in 2010 equal to 100. The latter includes barley, maize, rice and wheat also with value in 2010 normalized to 100. The data spans from January 2007 to June 2015 with observations $T = 102$. Natural logarithm of the grain index and energy index are denoted as $e_t = \log(E_t)$ and $g_t = \log(G_t)$. The plots of monthly values and log values for grain and energy indices are shown in Fig.3.1 The summary statistics for the e_t and g_t as well as their respective first differences Δe_t and Δg_t are shown in Table.3.1. As expected for most of the commodity price and return series, the indices series are volatile and the returns are not significantly different from 0 and non-normal as indicated by Jarque-Bera test.

In order to conduct cointegration analysis, one must examine the order of integration of variables in hands. Only if the variables are integrated of order one, will it be possible for the two variables to be cointegrated. Examining the order of integration without the knowledge of the underlying data generating process, three specifications of Augmented Dickey-Fuller

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[3] See `http://databank.worldbank.org/data/databases/commodity-price-data`

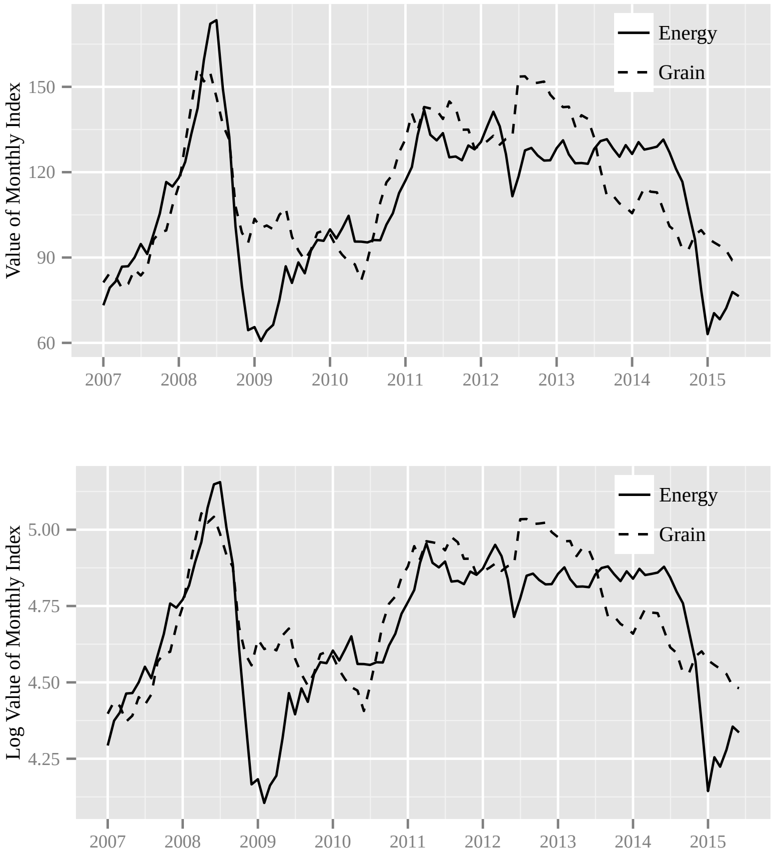

Figure 3.1: Monthly value and log value for Grain and Energy Index

tests Dickey and Fuller (1979) and Dickey and Fuller (1981) are conducted, namely one with trend and drift $\Delta y_t = a_0 + a_1 t + \gamma y_{t-1} + \varepsilon_t$, one only with drift $\Delta y_t = a_0 + \gamma y_{t-1} + \varepsilon_t$ and one without drift o trend $\Delta y_t = \gamma y_{t-1} + \varepsilon_t$. Test statistics for null hypothesis $H_0 : \gamma = 0$ (Unit Root) are shown in Table 3.1. Phillips and Perron (1988) propose a non-parametric unit root test with null hypothesis of unit root by directly modifying the test statistics. Two specifications of Phillips-Perron test Phillips and Perron (1988) are also conducted, one with trend and drift $y_t = \mu + \beta(t - \frac{1}{2}T) + \alpha y_{t-1} + \varepsilon_t$ and one only with drift $y_t = \mu + \alpha y_{t-1} + \varepsilon_t$. Test statistics for null hypothesis $H_0 : \alpha = 1$ (Unit Root) are shown in Table 3.1. All of the tests fail to reject the null hypothesis of unit root in both the log series at level 10% but reject the null hypothesis of unit root in both of the first difference of both log series at level 1%, which indicates both of the log series are integrated of order one, i.e., $I(1)$ process.

3.4.2 Engle-Granger two-stage approach

The linear two-step cointegration approach from Engle and Granger (1987a) is linear in nature. First the long run equilibrium relationship between log of energy index e_t and log of grain index g_t is estimated with energy index assumed to be driving force. The estimate for the cointegrating coefficient $\hat{\beta}_1$ is 0.90700 with p value 0. The residuals is constructed and tested for unit root. The result for the second step for EG cointegration test is shown in Table 3.3 column 1. Both AIC and BIC choose the lag in $\Delta\hat{\epsilon}_{t-i}$, $p = 1$ to correct serial correlation. The residual from the second step $\hat{\varepsilon}_t$ does not show serial correlation as indicated by the p values of Ljung-Box tests at lag 4, 8, 12. Unit root estimate $\hat{\rho} = -0.14$ and it is significantly different from 0 at 1% level. Thus, cointegration of the log index of energy and grain is found by EG cointegration test.

3.4.3 Johasen's Method

After pretesting the variables for order of integration, the most common procedure of Johasen's method starts by estimating the so-called undifferenced or level data in a VAR model. Since the result is very sensitive to the lag in the VAR system, the maximum lag length is selected to be 12 in the

Table 3.1: Summary Statistics and Unit Roots Test

	log grain g_t	log energy e_t	diff grain Δg_t	diff energy Δe_t
mean	4.7248	4.6782	0.0008	0.0004
stde	0.1969	0.2415	0.0534	0.0763
mini	4.3718	4.1051	-0.1962	-0.2715
maxi	5.0539	5.1558	0.1475	0.1484
N	102	102	101	101
skewness	0.055	-0.599	0.017	-1.299
kurtosis	1.681	2.533	4.204	5.277
Jarque-Bera	__	__	6.103	50.205
p value	__	__	0.041	0
ADF with trend	-1.939	-2.415	-4.983^{***}	-4.21^{***}
ADF with drift	-2.149	-2.556	-4.846^{***}	-4.18^{***}
ADF with none	-0.07	-0.222	-4.871^{***}	-4.201^{***}
PP with trend	-1.758	-1.982	-6.434^{***}	-5.736^{***}
PP with drift	-2.16	-2.307	-6.461^{***}	-5.756^{***}

Note: (***) denotes significance at 1% For ADF test with trend and drift terms, critical values at 1%, 5% and 10% are -3.99 -3.43 and -3.13. For ADF test with only drift term critical values at 1% , 5% and 10% are -3.46, -2.88 and -2.57. For ADF test with only drift term critical values at 1% , 5% and 10% are -2.58 -1.95 -1.62. For PP test with trend and drift terms, critical values at 1%, 5% and 10% are -4.05 -3.45 and -3.15. For PP test with only drift term critical values at 1% , 5% and 10% are -3.49, -2.89 and -2.58.

VAR system which is deemed as reasonable for monthly data. Information criteria such as AIC and BIC suggest lag length is 3. I then turn to estimate the model in Eq.(14)[4].

In this study, there are two variables in the cointegration system, therefore there are only three possible cases for the number of rank. If the Rank(Π) = 0, there will be no cointegration relationship. If the Rank(Π) = 2, which means Π is full rank and the system will be stationary and will be no cointegration relationship. Therefore they are cointegrated if and only if one cointegrating vector is found. Without the knowledge of the underlying data generating process, both maximal eigenvalue statistic and trace statistic are utilized to test the rank under three specifications, namely trend $\mu + \Phi D_t$, constant μ, and none (see Eq.(14) & Eq.(15)). The result is in Table 3.2. The maximal eigenvalue statistics reject the $H_0 : r = 0$ against $H_a : r = 1$ at 5% significance level for constant and none specifications and at 10% significance level for trend model but fail to reject the $H_0 : r = 1$ against $H_a : r = 2$ at any conventional significance level. According to the sequential procedure, the null hypothesis $H_0 : r = 0$ (no cointegration) against $H_a : r > 0$ is rejected at 5% for models with constant and models with neither constant nor trend and 10% for models with trend. However, $H_0 : r \leq 1$ against $H_0 : r = 2$ is rejected at 10%. This finding may be due to the misspecification of the models with neither constant nor trend since $r = 2$ indicates the system is stationary, which is excluded in the pretest. In conclusion, both Johansen cointegration methods show strong evidence that the log series of energy index and grain index are cointegrated.

3.4.4 Threshold Cointegration

For nonlinear cointegration methods, both threshold autoregressive and momentum threshold autoregressive specifications are estimated with threshold values set to zero and consistently estimated with grid search method. The threshold estimation is conducted with the method of Chan (1993): threshold that minimizes the residual sum of squares in Eq.(16) is chosen i.e., $\hat{\tau} = \arg\min \sum \hat{\varepsilon}_t^2$. With maximum 12 lags, each lag specification is examined to find out the consistent estimate of the threshold.

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[4] Estimating Eq.(14) or Eq.(15) in fact will return the same estimate of Π. The only difference lies in the interpretation of the estimate

Table 3.2: The λ_{trace} and $\lambda_{\max}$ Tests for the Rank(Π)

H_0	H_a	Specification	Statistic	Critical Value		
				10%	5%	1%
λ_{trace} test						
$r \leq 1$	$r = 2$	Trend	7.036	10.49	12.25	16.26
$r = 0$	$r > 0$		24.218*	22.76	25.32	30.45
$r \leq 1$	$r = 2$	Constant	6.674	7.52	9.24	12.97
$r = 0$	$r > 0$		23.343**	17.85	19.96	24.6
$r \leq 1$	$r = 2$	None	6.673*	6.5	8.18	11.65
$r = 0$	$r > 0$		23.306**	15.66	17.95	23.52
$\lambda_{\max}$ test						
$r = 1$	$r = 2$	Trend	7.036	10.49	12.25	16.26
$r = 0$	$r = 1$		17.182*	16.85	18.96	23.65
$r = 1$	$r = 2$	Constant	6.674	7.52	9.24	12.97
$r = 0$	$r = 1$		16.669**	13.75	15.67	20.2
$r = 1$	$r = 2$	None	6.673	6.5	8.18	11.65
$r = 0$	$r = 1$		16.633**	12.91	14.9	19.19

Note: (*), (**) and (***) denotes significance at10%, 5% and 1%. $\lambda_{\max}$ refers to max.

In order to correct for serial correlation in the residuals in the nonlinear adjustment path in Eq.(16), maximum of 12 lags in the first difference of the first step residuals $\Delta\hat{\epsilon}_{t-i}$ are added. Given the same sample available, adding lags as additional explanatory variables into the model will reduce the number of usable observations in the sample and model selection criteria such as AIC and BIC[5] tend to prefer the model with most lags. Therefore during the model selection process, the first 12 observations were kept out of the sample in order to apply the same number of usable observations when estimating model with different numbers of lags. Otherwise, alternative models with different lag specifications could not be adequately compared since information criteria in essence trade off between goodness of fit and flexibility holding the sample size fixed. It turns out AIC prefers model with 2 lags in $\Delta\hat{\epsilon}_{t-i}$ while BIC selects model with only 1 lag for all four nonlinear specifications. Of the two criteria, the SBC has superior large

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[5] $\text{AIC} = T \cdot \ln(\text{sum of squared residuals}) + 2p$,$\text{BIC} = T \cdot \ln(\text{sum of squared residuals}) + p \cdot \ln(T)$, where T is the number of usable observations and p is number of parameters estimated.

Table 3.3: Linear and Non-linear Cointegration Result for Energy and Grain Indices

Model	Engle-Granger	TAR		Consistent TAR		MTAR		Consistent MTAR	
Lag in $\Delta\hat{\epsilon}_t$	1	1	2	1	2	1	2	1	2
Estimate									
τ	NA	0	0	0.141	0.141	0	0	-0.051	-0.051
ρ or ρ^+	-0.14^{***}	-0.13^{**}	-0.145^{**}	-0.217^{***}	-0.232^{***}	-0.119^{**}	-0.138^{**}	-0.084^{**}	-0.098^{**}
	(-3.448)	(-2.353)	(-2.532)	(-3.397)	(-3.55)	(-2.129)	(-2.34)	(-2.019)	(-2.229)
ρ^-	NA	-0.112^{**}	-0.127^{**}	-0.07	-0.085^{*}	-0.122^{**}	-0.132^{**}	-0.282^{***}	-0.286^{***}
		(-2.109)	(-2.329)	(-1.506)	(-1.772)	(-2.323)	(-2.492)	(-3.292)	(-3.318)
Diagnostics Test									
AIC	-261.521	-309.406	-304.97	-312.912	-308.496	-309.348	-304.918	-313.804	-308.896
BIC	-253.647	-298.985	-291.994	-302.491	-295.52	-298.927	-291.942	-303.383	-295.921
$Q_{LB}(4)$	0.555	0.954	0.997	0.963	0.997	0.956	0.997	0.926	0.998
$Q_{LB}(8)$	0.784	0.96	0.995	0.937	0.988	0.963	0.995	0.926	0.987
$Q_{LB}(12)$	0.876	0.988	0.994	0.993	0.999	0.988	0.993	0.945	0.97
Hypothesis Testing									
$\Phi(H_0 : \rho^+ = \rho^- = 0)$	NA	4.893	5.561^{*}	6.798^{*}	7.485^{**}	4.862	5.533^{*}	7.294^{*}	7.708^{*}
p value^a		[0.1046]	[0.0594]	[0.0576]	[0.0314]	[0.1408]	[0.0827]	[0.0850]	[0.0576]
Critical Value (1%)^b		8.28	7.99	9.32	9.10	8.79	8.51	10.62	10.43
Critical Value (5%)^b		5.96	5.81	7.01	6.82	6.49	6.26	8.16	7.93
Critical Value (10%)^b		4.95	4.83	5.93	5.78	5.42	5.25	7.00	6.80
$F(H_0 : \rho^+ = \rho^-)$		0.057	0.056	3.521^{*}	3.503^{*}	0.001	0.006	4.421^{**}	3.902^{*}
p value		[0.811]	[0.813]	[0.064]	[0.064]	[0.974]	[0.937]	[0.038]	[0.051]

Note: (^{a}), (^{b}) denote p values and critical value obtained from our monte carlo simulation with sample size $T = 102$ and replication $N = 50000$ following procedure in Enders and Siklos (2001).
(*), (**) and (***) denotes significance at 10%, 5% and 1%.

sample properties. the BIC is asymptotically consistent while the AIC is biased toward selecting an overparameterized model. However, in small samples, the AIC can work better than the BIC (Enders, 2015). Without further knowledge, 8 specifications with 1 or 2 lags are estimated with the original sample size and the result is reported in Table 3.3. It should be noted that 1 or 2 lag specifications choose the same consistent threshold 0.141 in consistent TAR, so does consistent MTAR models with -0.051. Among all models with lag 1 or 2, both AIC and BIC choose MTAR adjustment with consistently estimated threshold with 1 lag to be the best model with lowest values -313.804 and -303.383. Diagnostic checking does not find serial correlation in $\hat{\varepsilon}_t$ the as suggested by the high p values of Ljung-Box tests at lag 4 , 8 , and 12.

The necessary and sufficient conditions for the stationarity of $\{\hat{\epsilon}_t\}$ that $\rho^+ < 0$, $\rho^- < 0$ and $(\rho^+ + 1)(\rho^- + 1) < 1$ are satisfied by all the estimated models. Most of the estimates are significantly different from 0 at conventional level. The null hypothesis of no cointegration $\rho^+ = \rho^- = 0$ with p value 0.0850 indicate log energy index and log grain index are cointegrated non-linearly with momentum threshold adjustment. The hypothesis of symmetric price transmission is rejected at 5% level. Focusing on the point estimates of the adjustment parameters of the best model selected, $\hat{\rho}^+ = -0.084$ suggests the positive deviations from long run equilibrium above the threshold -0.051 due to either increase in grain index or decrease in energy index or both are closed up only by 8.4% per month while the $\hat{\rho}^- = -0.282$ indicates the negative deviations resulting from either increase in energy index or decrease in grain index or both are eliminated by 28.25% per month. If measured by time, it take less than 4 months to absorb the negative shock while positive shock takes nearly 12 months to be fully digested. This result suggests the input-output story of biofuel production where biofuel is the substitute good for fossil fuel and once the price of input (biomass such as grain) increases or the price of output (biofuel) decreases or both happens, the widened markup is eliminated faster than squeezed markup is closed up under the cases of either increases in the input price or the decreases in the output price or both. Biofuel producers are more willing to increase the output to meet the higher demand in case of increase in energy price but find it difficult or are reluctant to reduce the quantity when the opposite happens.

3.4.5 Bi-variate Error Correction Model

As discussed in the result of threshold cointegration, the momentum threshold autoregressive model with consistently estimated threshold and one lag is selected to be the best model by the information criteria. Therefore the short run dynamics is analyzed with bi-variate error correction model with threshold incorporated. The estimation result is reported in Table 3.4. Diagnostic checking such as Ljung–Box Q test at lag 4, 8, and 12 rule out the possibility of serial correlation in $\hat{\vartheta}_{nt}$ and $\hat{\vartheta}_{gt}$ at any conventional levels. R^2 for the grain and energy models are 0.215 and 0.286 and F-stat for these two equations are 4.249 and 6.203 with p values 0. AIC for energy equation and grain equation are -249.57 and -311.035. BIC for energy equation and grain equation are -228.729 and -290.194.

Both positive and negative adjustment parameters are not significant in the error correction model for energy index. However, only the negative but not the positive adjustment parameter in the error correction model for grain index is significant with a negative sign. The signs of all four point estimates are as expected. It has economics implication that energy price index is not responding to the short run disequilibrium in a systematic way. Moreover, once the system departs from equilibrium due to negative shock, grain price will restore the system back to long run equilibrium while positive deviation will not trigger such restoration in a statistical sense. Therefore error correction model implies that in the short run widened markup only triggers increase in grain price but not the decrease in the energy price. In the grain equation, lags of both positive and negative changes in energy price are significant but the lags in grain price changes are not while in the energy equation, only negative change in grain price is significant. Having noted that, it might be surprising that Granger causality test for both series rejects self causality but fails to reject cross causality e.g., $H_0(\alpha_i^+ = \alpha_i^- = 0, \forall i)$ in grain equation means null hypothesis that lagged change in grain price does not Granger cause change in grain price. This may be due to the difference between the joint test and multiple single restriction tests stacked over. The most important test is the momentum equilibrium adjustment path asymmetry test $H_0(\delta^+ = \delta^-)$. For grain equation, F-statistic is 2.766

Table 3.4: Threshold Incorporated Bi-variate Error Correction Model Estimation Result for Energy and Grain Indices

	Grain Δg_t		Energy Δn_t	
Estimate				
θ	-0.002	[0.869]	0.014	[0.246]
δ^+	-0.036	[0.391]	0.082	[0.156]
δ^-	-0.2^{**}	[0.028]	0.163	[0.183]
α_1^+	-0.102	[0.519]	0.074	[0.729]
α_1^-	-0.056	[0.609]	0.582^{***}	[0]
β_1^+	0.507^{***}	[0.002]	0.187	[0.399]
β_1^-	0.475^{**}	[0.021]	0.199	[0.47]
Diagnostics Test				
R^2	0.215		0.286	
AIC	-311.035		-249.57	
BIC	-290.194		-228.729	
F-stat	4.249	[0.001]	6.203	[0]
$Q_{LB}(4)$	3.745	[0.442]	5.926	[0.205]
$Q_{LB}(8)$	11.059	[0.198]	7.900	[0.443]
$Q_{LB}(12)$	15.864	[0.198]	9.050	[0.699]
Hypothesis Testing				
$H_0(\delta^+ = \delta^-)$	2.766^{*}	[0.09]	0.371	[0.54]
$H_0(\alpha_i^+ = \alpha_i^- = 0, \forall i)$	11.141^{***}	[0]	0.913	[0.4]
$H_0(\beta_i^+ = \beta_i^- = 0, \forall i)$	0.521	[0.6]	9.547^{***}	[0]
$H_0(\Sigma\alpha_i^+ = \Sigma\alpha_i^-)$	0.012	[0.91]	0.001	[0.98]
$H_0(\Sigma\beta_i^+ = \Sigma\beta_i^-)$	0.045	[0.83]	2.893^{*}	[0.09]

Note: (*), (**) and (***) denotes significance at 10%, 5% and 1%. Numbers in square bracket in the third and fifth columns are p values.

with p value 0.09, which rejected symmetric on grain equation. Although it seems marginally significant, this together with the F-statistic 0.371 with p value 0.54 for the same test in the energy equation may point out a striking finding that grain price is responding to the disequilibrium systematically with momentum equilibrium adjustment path asymmetry.

3.5 Conclusion

As of 11 Jan 2016, the Cushing, OK WTI Spot Price FOB has plunged to USD $30.14 per barrel, back to the nominal level in 2003 after its peak over $140 in 2008. This crash seems to discourage the development of biofuel industry. However, given the foreseeable depletion of the fossil fuel, this temporal disincentive may only weaken the link between grain and energy but will not terminate the searching for alternatives such as solar, nuclear power. This chapter investigates long run price dynamics between global grain and energy indices with the linear co-integration and threshold co-integration. Short run price adjustment is also addressed with error correction model with threshold and momentum. Compared with the existing literature, this chapter utilizes global grain and energy price indices series instead of particular commodity products or instrument due to the following reasons: first particular commodity products or instruments such as commodity future could be noisy due to other factors such as market microstructure, speculation; second, the indices selected represent general global price levels without suffering from any geographical bias or unnecessary complication stemming from price dynamics interaction of various commodity products.

There are several worth noting conclusions. First, global energy price index and global grain index are cointegrated. This result is first shown by the traditional linear cointegration methods and later by non-linear cointegration methods. This is in line with the findings in most of the existing empirical literature and the implication of the theoretical model. Second, the energy price seems to evolve more independently than grain price does. This finding is not only supported by the insignificant estimates of adjustment parameter in the error correction model in energy equation but also suggested by the Granger Causality test. This is consistent with the notion that energy price is mainly driven by its fundamentals such as supply and demand while food agricultural commodity could also be affected by derived demand such as production of biofuel. Third, asymmetry exists in the cointegration in many ways. In the long run, disequilibrium adjustment responds asymmetrically to previous positive or negative deviation in the MTAR cointegration. In the short run examined with the error correction model with MTAR cointegration, the asymmetry exists in the short run adjustment only shows in the grain series. This chapter also points out the gap in the existing literature regarding the lack of sufficient theoretical explanation for the asymmetry.

Besides the findings discussed above, this chapter uniquely contributes to the literature mostly by casting light into the debate of long run equilibrium of energy market and agricultural market. It suggests the disagreement of the literature may result from the ignorance of asymmetry of the adjustment process as pointed out in the econometrics literature. On top of that, the findings in this chapter are also in line with the story of agricultural production cost, theory of market power, adjustment and menu cost of biofuel production as discussed in the introduction and literature review sections.

Chapter 4

Essay Three: Extreme Event Studies in Commodities Markets

4.1 Introduction

Commodity is one of the most important asset class and investment class in the modern global economy and financial market. While it is fundamental to well-being and growth of the economy as input for production and essential to the welfare of people as a consumption good, it is also the indicator of the health of the global economy as commodity prices reflect the changes in the demand while the supply tends to be stable. The global oil price has never reached \$40 per barrel before 2004, and it peaked at \$145 in July 2008 before returning to a low level at around \$30 in 2015. Similarly, corn price has also witnessed its several historical peaks in around 2007 and 2011 during food crisis. High energy price has been blamed for driving up the agricultural commodity price. The dynamics between commodity prices are worth studying, and the literature on the relationship between these commodities is rich. However, most of these existing literature fails to capture the dynamics in the tails or the extreme values, and thus we utilize modified event study methodology to ask a question how different is the dynamics in the extreme from that in the normal levels.

Economists are often asked to measure the impact of one variable have on other variables. Most of the tools should be taken care of to address the difference between causality and association when the variable assumed to exogenous turns out to be endogenous. The variable of interest here is usually measurable and observed together with other variables at the same frequency in time series setting. When it comes to the impact of an event, if the event of interest is a once-in-a-life-time event, it is often difficult, if not purely impossible, to isolate the effect of other concurrent events or variables. However, if the event occurs at a regular basis, event study methodology could be of help as gathering the similar events can average out the effect of other events or variables. If the occurrence of an event is further assumed or suggested by theory to be exogenous, the causal interpretation could be established. In this chapter, a modified event study methodology is conducted with bootstrap inference. It examines how the price of one commodity respond to the extreme price changes in other commodities, how these impacts from the extreme returns accumulate along time, whether particular pattern or signal arise before these extreme returns and whether asymmetry exists in the response patterns.

The next section is on literature review. In section 4.3, methodology and models applied in this chapter are discussed. This is followed by the estimation result suggesting different interactions of commodities between extreme days and normal days and heterogeneity in the responses to extreme events. The chapter ends with the conclusion and the potential contribution.

4.2 Literature Review

Event study methodology originates from corporate finance literature to address the impact of a corporate event or financial related episode on the security prices, returns and other trading activities. The earliest work dates back to Dolley (1933), which studies the impact of stock split on stock prices and event study later became a popular workhorse in late 1960's with the development of capital asset pricing model and risk factor modeling to isolate the effect that is not coming from the event under study. The corporate event includes the usually studied earning announcement, mergers and acquisitions announcement, and change top management and even the less frequent events such as product recall announcement and the death in top management. Also it cast light on the efficient market hypothesis (EMH) in its semi-strong form by capturing how the information flows into stock price. The semi-strong EMH asserts market participants will take advantage of all publicly available information and the price of the security incorporates all publicly available information, and thus is not predictable consistently based on public information available at this moment. Consequently, new coming information will have an immediate impact on the market. Thus testing the EMH can rely on examining either the reaction of security to arriving news or the predictability and profitability over normal return with publicly available information. Event study lies in the former in that returns around the event are examined to cast light on the properties of security reaction to the news by showing the speed of adjustment of prices to information.

However, the event here could be an economics event or non-economics event ranging from wars to natural disasters, aircraft crash or even terrorist attacks. Chen and Nguyen (2013) study the impact of terrorist and military attacks on global capital markets. Maloney and Mulherin (2003) investigate the impacts of the crash of Challenger on the four NASA contractors and stock markets in the period immediately following the crash seemingly singled out the firm that manufactured the faulty component while it took an esteemed panel several months. As discussed in MacKinlay (1997) event studies methodology has been applied beyond the topic of market efficiency to a broader spectrum of areas:

> "In accounting and finance research, event studies have been applied to a variety of firm specific and economy wide events. Some examples include mergers and acquisitions, earnings announcements, issues of new debt or equity, and announcements of macroeconomic variables such as the trade deficit. However, applications in other fields are also abundant. For example, event studies are used in the field of law and economics to measure the impact on the value of a firm of a change in the regulatory environment and in legal liability cases event studies are used to assess damages."

Creatively, Fisman (2001) uses several adverse rumors about the state of Suharto's health and compare the returns of firms with differing degrees of political exposure to estimate the value of political connections.

To address the impact of corporate events on stock prices, the abnormal return has to be estimated first by removing normal (expected/predicted)

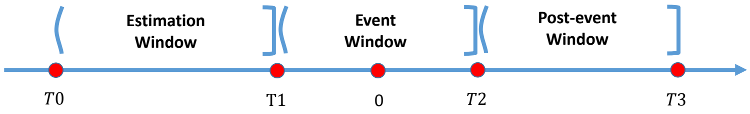

Figure 4.1: Time line for event study

return. Denote the return of firm as R_{it}, and the return of broad stock market index as R_{Mt}, where returns are defined as logarithmic returns, the natural logarithm of the current to previous price ratio. Most frequently used market index model runs simple linear regression $R_{it} = \alpha + \beta R_{Mt} + e_t$, $t = -n-5, -n-4..., -6$ chosen as estimation window before the event day $t = 0$. Several trading days right before the event day are usually kept out of the estimation window to avoid contamination due to information leakage prior to the official announcement. Abnormal returns series is defined as the difference between actual returns and conditional expected returns given the market return, *i.e.* the residuals from the regression $AR_{it} = R_{it} - E(R_{it}|R_{Mt}) = R_{it} - \hat{\alpha} - \hat{\beta} R_{Mt}$, where $\hat{\alpha}$ and $\hat{\beta}$ are the OLS estimates. Later, the abnormal return on the event day AR_{i0} and returns in the event window are assessed for statistical significance[1] with the distribution of the abnormal return in the control period.

In fact, normal returns can be detected in various ways with each relying on a specific model to determine the conditional expected return given the market conditions or characteristics of individual firms. Extending the single factor model such as the market index model to multi-factor can reduce the standard error of the regression $\hat{\sigma}_e^2$ and hence the variance of the distribution of the abnormal return.

Unlike the application in corporate finance, event related research does not have a huge literature in the commodity market with few exceptions. In the global energy market, the price of crude oil is mainly driven by supply and demand. Two of the notable events related to crude oil fundamentals are Organization of the Petroleum Exporting Countries (OPEC) conference announcements and U.S. Strategic Petroleum Reserve (SPR). Demirer and

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[1] $\text{Var}(AR_{i0}) = \hat{\sigma}_e^2 (1 + \frac{1}{n} + \frac{(R_{M0} - \bar{R_M})^2}{\sum_{h=-(n+5)}^{-6} (R_{Mh} - \bar{R_M})^2})$.

Kutan (2010) study the information content of OPEC conference announcements and SPR announcements in crude oil spot and future price with three normal return models and found asymmetry in that only OPEC production reduction announcements generates statistically significant impact. Persistence of returns are also found after OPEC production cut announcements. It explains that in good time with high oil price level, OPEC is more likely to agree on production increase and thus can be well anticipated by the market while in bad time, no change or production cut could be surprising. As for SPR, short run impact is found immediately following announcement date and its impact lasts for around a week. Lin and Tamvakis (2010) extend the investigation to both official conferences and ministerial meetings of OPEC and studied the effect under different price bands and found evidence of differentiation between light and heavy crude grades. Without conventional event study methodology, Schmidbauer and Rösch (2012) apply combination of regression and GARCH model with dummy variables indicating OPEC announcement. They find post-announcement effect on expectation, which is positive for cut decision and negative for increase or maintain decision. However, positive pre-announcement effect on volatility is strongest in the case of cut decision. It still fits into the story of most difficult agreement on production cut announcements in the bad days.

In the traditional event studies, the event of interest is an identifiable event at a given time by nature. However, this convention limits the scope of questions as some event is not observable but may share common characteristics. Besides, a traditional event study is model dependent in that it requires a pricing model as a benchmark for assessing normal returns, which makes a joint hypothesis problem even though multiple models can be employed for robustness check. Patnaik, Shah, and Singh (2013) propose a modified event study methodology focused on tail events to study the stability of financial globalization. With domestic and foreign equity market returns, capital flow and foreign exchange rate return series, the impact of extreme values or tail events in one series on others are examined with bootstrapping inference to suggest that financial globalization has not induced instability on the domestic equity market. This modified event study methodology is utilized in this chapter to examine the dynamics of the commodity market.

Most of the empirical papers concerning the dynamics of fuel and agricultural commodity mainly utilize two kinds of models, VAR/VECM and Computable general equilibrium (CGE) models (Qiu, Colson, and Wetzstei, 2011). The former types of models enjoy popularity due to its convenience in illustrating the dynamics and interaction of the system and the flexibility in measuring short term or long term impacts. The latter methodology gains an edge when there is only limited data points. However, it suffers more from assumption of model parameters and difficulty in distinguishing short-run and long-run impacts. For studies with time series models, the finding on fuel and agricultural commodity dynamics is mixed. Cointegration between crude oil and corn, soybean, and wheat as well as causality stemming from energy to agricultural commodity is found in Saghaian (2010). However, Nazlioglu and Soytas (2011) focus on global oil prices and domestic agricultural commodity price in Turkey and the result suggests neutrality of agricultural commodity markets both in the short-term and in the long-term. Zhang, Lohr, Escalante, and Wetzstein (2010) also find no direct long-run and limited short-run impact of fuel on agricultural commodity with cointegration technique. With a structural VAR model, Qiu et al. (2011) conclude the main driving forces of food price in the long run are fundamental factor such as demand and supply while biofuel production only has short run but not long-run price shift of food related commodity. Unlike the research mentioned above with conclusive positive or negative findings, some studies point out inter-relationship between fuel and agricultural commodity dynamics could be dependent on time period, region or type of commodity (Campiche et al., 2007; Ciaian and Kancs, 2011a; Natanelov, Alam, McKenzie, and Van Huylenbroeck, 2011; Rosa and Vasciaveo, 2012). Similar to one of the findings in this chapter, different magnitudes of the responses of commodity prices to positive or negative price oil price changes are found in Wixson, Katchova, Wixson, and Katchova (2012).

Although dynamics and interaction among commodity have been studied extensively with VAR type of model, those studies employ data with the full spectrum of return space without distinguishing normal days and extreme days. Also, monthly or weekly spot price are the main data for these studies partly because non-price series such as inventory, production, and price deflator are not available in higher frequency. However, it is possible that the shocks of different magnitudes have different impact per unit on other series. This chapter thus carries out modified extreme event study of Patnaik et al. (2013) to examine the response of commodities to extreme shocks in comparison of traditional impulse response.

4.3 Methodology

The method employed in this chapter can be interpreted as cumulative returns along the event window conditional on the tail events of other series. It keeps tracks of the behavior of the return when the other market is extremely unusual in term of return. If instead of focusing on the tail events, it expands the events of interest to the whole distribution of return, one can easily imagine the analysis degenerates to the unconditional cumulative returns with overlapping windows, which is just representing the general trend of series over the sample period. Thus unusual pattern around the event must carry some information about the dynamics of the tail events between the series under study.

4.3.1 Uncontaminated Event

Consider return series $\{r_{jt}\}_{t=1}^{T}$, the upper quantile is calculated as $Q(r_j, q)$ $s.t.$ $\Pr(r_j > Q(r_j, q)) = q$, and denote the upper tail events as $E_j^+ = \{i\}$ $s.t.$ $r_{ji} > Q(r_j, q)$. Same procedure for lower quantile yields E_j^-. Together, the extreme event days for return series r_j is $E_j = E_j^+ \cup E_j^-$, which contains all the date with extreme positive and negative returns and are identified as events of interest. The dates w trading days before or after any particular event m are defined as event windows associated with event m. It defines uncontaminated extreme event in the upper tail E_{uj}^+ s.t. $m \in E_{uj}^+$ where $m + k \notin E_j$ $\forall k \in \{-w, -w+1, \cdots, -1, 1, \cdots w\}$. In other words, if all the dates in the event window associated with extreme event date m are not extreme event in tails of either side, then event date m is uncontaminated. Explained intuitively, when perception or expectation of market participants change rapidly due to new information flow, extreme events from both sides could cluster and the uncontaminated event set allows for isolation of impact from other positive or negative events. Event set E_j is potentially contaminated, and it includes uncontaminated event set as a subset, $E_{uj} \subseteq E_j$.

4.3.2 Runs of Extreme Event

If R consecutive returns $\{r_{jt}\}_{t=n+1}^{n+R}$ happen to lie in the same tail, returns in these days are then fused into a single return $\sum_{t=n+1}^{n+R} r_{jt}$.[2]The logic here is that the run of extreme returns assumed to be affected by the same source of force. Without this specification, there will be R overlapping moving windows and potentially multiple capturing impacts if they are studied as separate events individually. Similar to the definition in uncontaminated event, uncontaminated run of event of length R in upper tail is those consecutive dates $\{n+1, \cdots n+R\} \in E^+$, where $n+R+k \notin E$, $\forall k\{1, \cdots w\}$ and $n-l \notin E$, $\forall l\{1, \cdots w\}$. The similar definition applies to uncontaminated runs of events in the lower tail. The uncontaminated runs of events are then studied along with the uncontaminated event.

4.3.3 Bootstrap Inference

Traditional event studies as discussed in session 4.2 relies on specific model to compute abnormal returns. As illustrated in Figure 4.1, the days several days away from the identified event are used as estimation window, and the normal return is estimated with a model. Abnormal return during the event window is calculated as the difference between the actual return and normal return. The abnormal return series in the event window are lined up with the event time and tested for statistical significance under a certain distributional assumption. Such distributional assumption may undermine the validity of event study besides the possibility of serial correlation since error will occur in the statistical inference once the assumption is violated.The bootstrap method I employed in this chapter is as follows:

1. For event set E_j with size $|E_j| = N_j$ associated with return series $\{r_{jt}\}_{t=1}^{T}$, and each event with window of length $2w+1$. To study the behavior of returns series in event day or the impact of cross series extreme event, the cumulative return series for return series $\{r_{kt}\}_{t=1}^{T}$ is denoted as $\{CR_{i,kt}\}_{t=i-w}^{i+w}\ \forall i \in E_j$, where $CR_{i,kt} = \sum_{t=i-w}^{t} r_{kt}$. The

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[2] All the returns are continuously compounded returns.

cumulative return series is then averaged across all N_j event dates to yield an average cumulative return series $\{C\bar{R}_{kt}\}_{t=-w}^{w}$

2. Sampling from cumulative return series $\{CR_{i,kt}\}_{t=i-w}^{i+w} \forall i \in E_j$ with replacement N_j times gives bootstrap return series and is then averaged to yield $\{C\bar{R}_{kt}^{b}\}_{t=-w}^{w}$ which is considered a draw from the distribution of average cumulative return.

3. The procedure in step 2 is repeated for 1000 times and the corresponding 1000 bootstrap average cumulative return is used to compute the percentile of the distribution for the average cumulative return in each day in the event window. The percentile is later used as confidence intervals for inference.

Bootstrap applied in this chapter avoids making specific assumption on distributions but it instead resamples the empirical price paths. After identifying extreme events in one series, it collects the return series of another returns around these event dates. Then it re-samples from the collection for a specified times. This bootstrap inference can thus help to increase statistical efficiency without assumptions in classic inference procedure.

4.3.4 Generalized Impulse Response

Impulse response function is usually tracking the impact of any variable on others in the system across time derived from a vector autoregressive model or vector error correction model. It is essential tools in causal analysis and policy effectiveness. Impulse response examines the dynamics by converting the VAR into a vector moving average and identify the dynamic properties of the VAR from the parameters of the VMA. Assume Y_t is a k dimensional demeaned vector series with VAR specification $Y_t = A_1Y_{t-1} + \cdots A_pY_{t-p} + U_t$ and equivalent VMA representation $Y_t = \Phi(B)U_t = \sum_{i=0}^{\infty} \Phi_i U_{t-i}$ where $\Phi_{jk,i}$ represents the response of variable j to $u_{k,t-i}$, a unit impulse in variable k from i^{th} period ago. Ceteris paribus argument fails here since $\Sigma = E[U_tU_t^T]$ is usually non-diagonal and thus it is hardly likely to generate a unit shock in any particular variable without transformation. Cholesky decomposition applied to covariance matrix yields $\Sigma = PP^T$, where P is a lower triangular matrix. Then VMA representation is transformed into $Y_t = \sum_{i=0}^{\infty} \Theta_i w_{t-i}$

where $\Theta_i = \Phi_i P$, $w_t = P^{-1} U_t$, and $E[w_t w_t^T] = I$. Impulse response function is thus defined as

$$\varPsi_j^o(n) = \Phi_i P e_j,\ n = 0, 1, 2, \ldots$$

where e_j is a vector with 1 in its j^{th} entry and 0 in others. Although this facilitates ceteris paribus argument, it suffers from variables ordering as it implies recursive contemporaneous relationships among the variables in Y_t.

The modified extreme event study (EES) methodology applied in this chapter has analogies with impulse response function as pointed out by Patnaik et al. (2013). They consider the extreme event studied as IRF of a VAR at the tail. They conduct Monte Carlo simulation with two cases, one case with two white noise series and the other case with a relationship in the tail only. Both IRF and extreme event methodology are applied in both cases. The graph in page 231 of Patnaik et al. (2013) shows similar result for IRF and extreme event methodology in the case of white noise but a striking difference in the case with the relationship in the tail. The latter case, IRF shows no response, while extreme event methodology picks up the shock to tail event.

As a comparison with the result in the EES, generalized impulse response function (GIRF) proposed by Pesaran and Shin (1998) is applied, which is immune from the variables ordering issue as traditional IRF. For system $X_t = \sum_{i=1}^{p} A_i X_{t-i} + U_t = \sum_{i=0}^{\infty} \Phi_i U_{t-i}$, where $\Phi_i = \sum_{j=1}^{p} A_j \Phi_{i-j}$ and $\Sigma = E[U_t U_t^T]$. It is defined as $GIRF(n, \delta_j, \Omega_{t-1}) = E(X_{t+n} | u_{jt} = \delta_j, \Omega_{t-1}) - E(X_{t+n} | \Omega_{t-1})$. Assuming multivariate normality for U_t yields $E(U_t | U_{jt} = \delta_j) = (\sigma_{1j}, \sigma_{2j}, \cdots, \sigma_{mj})' \sigma_{jj}' \delta_j = \Sigma U_j e_j \sigma_{jj}^{-1} \delta_j$ and scaled GIRF as $\varPsi_j^g(n) = \sigma_{jj}^{-1/2} \Phi_n \Sigma U_j,\ n = 0, 1, 2, \cdots$.

4.4 Results

4.4.1 Data

Most of the existing literature utilize monthly data or weekly data on commodity wholesale price or aggregated prices to capture the dynamics with VAR/VECM type of model. However, in this chapter, prices of future contract with non-adjusted price based on spot-month continuous contract calculations is used. The use of future contract has both advantage and disadvantage. On one hand, future market serves a function for price discovery, and it is argued that if there exist a dynamics interaction or equilibrium between the prices of the commodity, arbitrage opportunity could be seized in a more efficient way with future market due to its liquidity and volume. Besides, cash prices of commodity tend to be more volatile and noisier because spot price reflects current supply and demand for delivery pressure. On the other hand, use of future contract suffers from data non-synchronization issue. Future contracts are traded in the exchange and even within the same exchange, not all the futures are traded in any given day. In this chapter, future contracts on agricultural and energy commodities include CBOT Corn Futures #1 (C1), ICE Sugar No. 11 Futures #1 (SB1), NYMEX WTI Crude Oil Futures #1 (CL1), ICE Brent Crude Oil Futures #1 (B1), NYMEX Natural Gas Futures #1 (RB1) and Ethanol Futures, Continuous #1 (EH1). Sample period for all data except ethanol spans from Jan 1st, 1994 to Dec 31st, 2015. Due to data unavailability, price on ethanol only dates back to Oct 4th, 2011.

As shown in Table 4.1, the numbers of observations for all contracts are not the same. To facilitate the analysis, a reasonable procedure for synchronization is necessary. The raw price data is the daily settlement price for future contract. Instead of first taking the daily continuously compounded returns and subset the returns with the common dates, the raw prices with common dates are merged before the continuously compounded returns are calculated. For example, during period $\{t\}_{t=s}^{s+4}$, with 2 contract settlement price series $\{p_t^a\}_{t=s}^{s+4}$ and $\{p_t^b\}_{t=s,s+1,s+3,s+4}$, p_{s+2}^a is deleted, the price of contact a when there is no corresponding price on contact b and the new price series is converted into return series. The rationale behind this choice is the assumption that the impact of new or shock on non-trading day accumulates.

In the table of summary statistics shown in Table 4.1, the signs of mean simply represent whether the price has gone up or down during the sample period, and the standard deviation is way larger than the magnitude of the mean, suggesting the mean is not significantly different from 0. The natural gas turns out to be the most volatile among all the series under study, which is often observed in market. Theoretically, commodity that cannot be stored or easily perishable such as electricity is more volatile since inventory can serve as a buffer to any surplus or deficit in the fundamentals. Among the

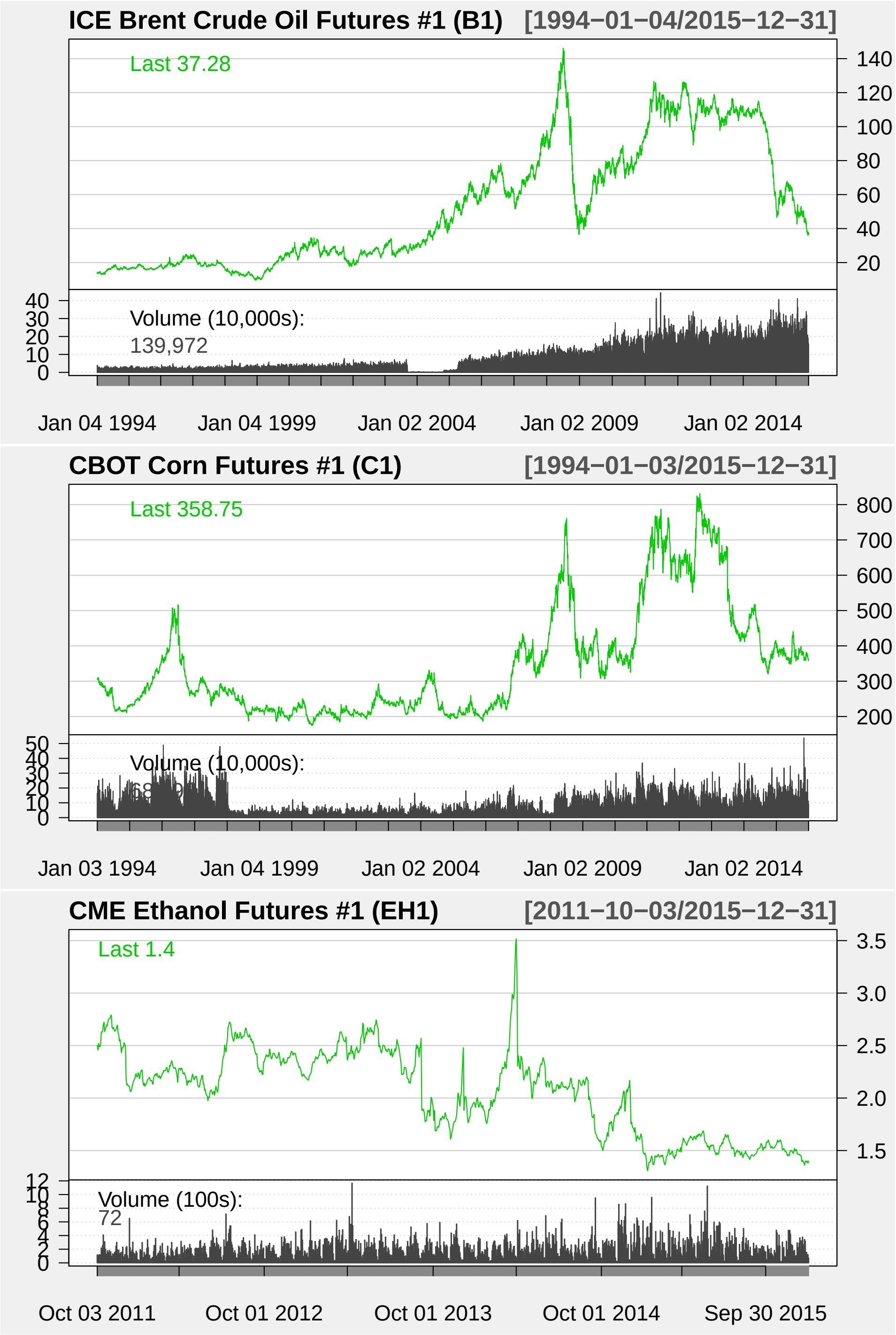

Figure 4.2: Plot for Settlement Price

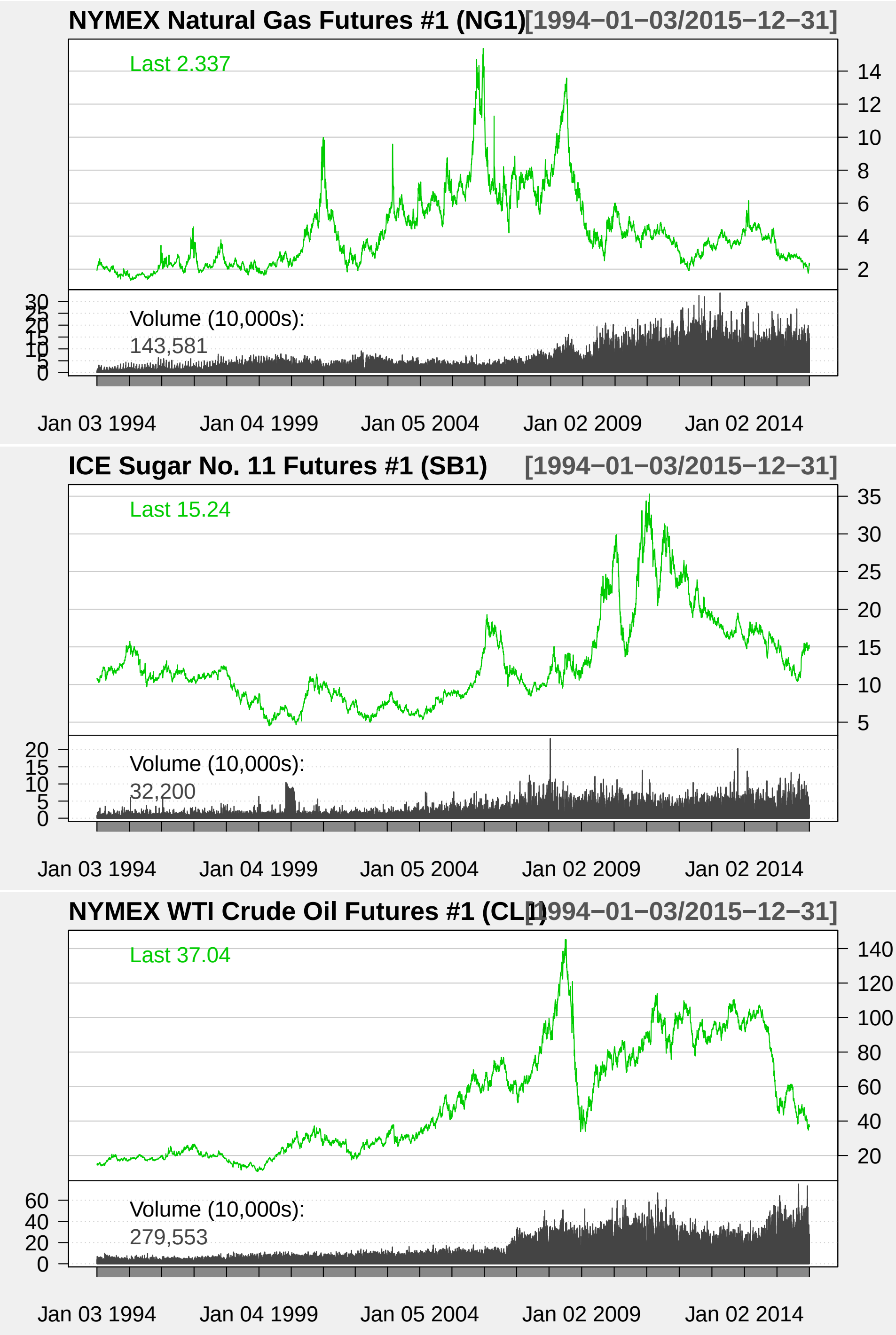

Figure 4.3: Plot for Settlement Price (cont'd)

Table 4.1: Summary Statistics for Daily Continuously Compounded Returns (%)

	N	Max	Q_{25}	Mean	Q_{75}	Median	Min	St.Dev.
Corn	5536	9.801	-0.932	0.003	0.913	0.000	-24.53	1.783
Ethanol	1061	7.501	-0.947	-0.055	1.050	0.072	-32.85	2.611
Gas	5511	45.76	-1.955	0.003	1.188	-0.038	-39.75	3.682
WTI	5519	16.41	-1.214	0.017	1.296	0.055	-16.55	2.341
Brent	5609	12.90	-1.098	0.018	1.144	0.074	-14.44	2.144
Sugar	5506	23.55	-1.079	0.006	1.135	0.000	-18.04	2.173

selected commodities, natural and crude oil require special and professional storage facility and thus the supply and demand for storage are also sources for the fluctuation of commodity prices.

4.4.2 Generalized Impulse Response

Generalized impulse response applied to these series with the sample period after Oct 4th, 2011 and the raw price data is again adjusted for synchronization. Akaike information criteria (AIC), Hannan-Quinn (HQ), Schwarz (SC) and forecast prediction error (FPE) chose the VAR model with lag of 1. The general impression of the generalized impulse response is that all the individual orthogonal shocks are visible at $t = 0$ and drop significantly at $t = 1$ before disappearing at $t = 2$. At first glance, this may surprisingly contradict to the findings of most of the existing literature with data with lower frequency. Most of the literature with lower frequency data find the impacts can last for months. It may be due to the efficiency of the future market in absorbing new information and thus eliminating the impact of the shock. The most distinct cross series responses are the ones between WTI crude oil and Brent crude oil in that both return series have similar response pattern to shocks from both return series. In fact, this finding is not surprising because no arbitrage argument could establish in theory cointegration between this two price series or the spread between this two prices should be stationary as these two prices a mainly driven by the same stochastic components and tend to move closely. Besides, corn and ethanol also have notable responses at $t = 0$ to the shocks from each other which could be explained by the fact that corn is the main input for a large portion of ethanol production globally. The most frequent critique of the impulse response is the incompleteness of the low dimension VAR system with omitted variables that are assumed to be in the shocks, but it serves here as a comparison with our extreme event study analysis.

4.4.3 Extreme Event Study

4.4.3.1 Event Characteristics

As discussed in the methodology section, unlike traditional event study, the event of interest here is the extreme returns in two tails given a probability chosen. The probability examined here is 5% in each tail. The probability may seem arbitrary at first glance but in fact, it is about the trade-off between identification of truly extreme returns and the adequacy of the sample size of extreme event. As a robust test, the same analysis with tail probability 2.5% are also conducted in each tail, and it yields similar pattern to those with 5% and the only difference is the larger magnitude with accumulative return on and after the event day with tail probability 2.5%. Table 4.2 shows the quantile in the both extreme events chosen for study. One should understand the extremum in the tail events might be different from the extremum in the whole return series because of certain criterion required for tail events as discussed in methodology session. With the chosen probability at 5%, Table 4.3 shows the number of events under examination for each of the series in both tails. Similar to conditional heteroskedasticity in the volatility or volatility clustering, the distribution of extreme returns are not evenly distributed over years as illustrated in Table 4.5 and 4.6.

The extreme returns in consecutive days are fused into runs of events as shown in Table 4.4. These four tables are related to each other in a particular way. Take corn return in bad days (lower tail) for example. 5% of the return sample yields 277 extreme returns in the total (see Table 4.3), 153 of which are un-clustered without any other extreme event within the event window. Among the 124 clustered events, 66 were used since they form runs of event (see Table 4.4 $23 * 2 + 4 * 3 + 2 * 4 = 66$). Therefore, the total events used in the analysis is $153 + 66 = 219$ with distribution over years of sampling period shown in Table 4.5. All the series share similar efficiency in utilizing the extreme returns for analysis as measured by the ratio of total

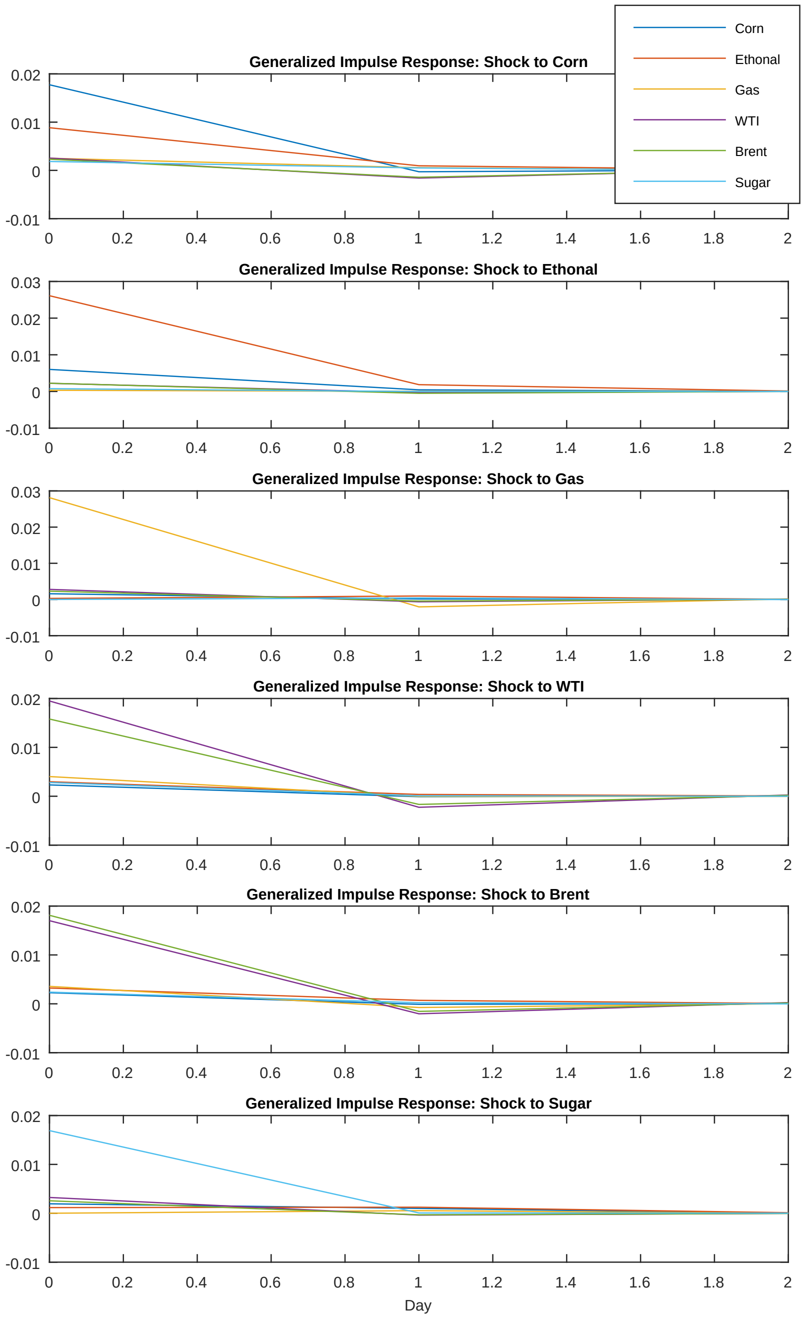

Figure 4.4: Generalized Impulse Response with VAR(1) model

Table 4.2: Quantile Values of Extreme Event

Daily Return (%)	Min	25%	Mean	Median	75%	Max
Lower Tail						
Corn	-25	-4	-4	-3	-3	-3
Ethanol	-14	-6	-5	-4	-4	-3
Gas	-20	-8	-7	-7	-6	-5
WTI	-17	-5	-5	-5	-4	-4
Brent	-14	-5	-5	-4	-4	-3
Sugar	-13	-5	-5	-4	-4	-3
Upper Tail						
Corn	3	3	4	4	5	10
Ethanol	3	3	4	4	5	6
Gas	6	6	8	7	9	32
WTI	4	4	5	4	5	14
Brent	3	4	5	4	5	13
Sugar	3	4	5	4	5	13

Table 4.3: Distribution of Event at 5%

	Un-clustered	Clustered			Total-used	Total
		Used	Removed	Total		
Lower Tail						
Corn	153	66	58	124	219	277
Ethanol	30	13	10	23	43	53
Gas	188	22	66	88	210	276
WTI	185	28	63	91	213	276
Brent	183	34	64	98	217	281
Sugar	180	32	64	96	212	276
Upper Tail						
Corn	184	32	60	92	216	276
Ethanol	28	13	12	25	41	53
Gas	194	10	72	82	204	276
WTI	188	28	60	88	216	276
Brent	205	17	59	76	222	281
Sugar	185	31	60	91	216	276

Table 4.4: Runs Distribution

Run Length	Two	Three	Four
Lower Tail			
Corn	23	4	2
Ethanol	5	1	0
Gas	8	2	0
WTI	14	0	0
Brent	17	0	0
Sugar	16	0	0
Upper Tail			
Corn	13	2	0
Ethanol	5	1	0
Gas	5	0	0
WTI	11	2	0
Brent	7	1	0
Sugar	14	1	0

used events to total events.

4.4.3.2 Response to Extreme Event

When interpreting the extreme event and response plot, one should accompany the analysis with the statistics of the tail returns as shown in Table. 4.2 as this enables one to gauge how extreme the events are and interpret cumulative returns of response series. The solid line in the plot represents the average over all the event cumulative returns across the event window, and the dashed line shows the bootstrapping 95% confidence interval. There are several points worth attention.

1. The estimate of the response in the event day represents the market reaction to the cross market extreme event or contemporaneous impact of the cross market shock in the tails. This interpretation may not be causal since the impact in the event day could be due to the same shock affecting the commodity market as a whole such as macroeconomic condition, but any visible impact can still demonstrate the link in the tail of the two returns series under study.

2. In the corporate event study setting, the irregular behavior such as

Table 4.5: Extreme Event Yearly Distribution

	Corn				Ethanol				Gas			
	5% good days		5% bad days		5% good days		5% bad days		5% good days		5% bad days	
	N	Median	N	Median	N	Median	N	Median	N	Median	N	Median
1994	3	4.400	6	-3.368					8	8.484	5	-6.624
1995	4	3.514	1	-4.303					6	7.164	5	-6.765
1996	2	3.071	8	-3.189					14	7.346	12	-7.831
1997	9	3.212	9	-3.074					6	7.220	12	-6.762
1998	10	3.423	6	-3.250					8	6.614	9	-6.576
1999	7	3.765	7	-3.138					10	6.695	8	-6.326
2000	7	3.904	8	-3.121					13	6.756	12	-6.972
2001	6	4.874	6	-3.183					12	7.703	22	-7.137
2002	12	4.193	4	-3.163					17	7.192	12	-6.008
2003	8	3.778	5	-3.337					12	8.350	10	-8.202
2004	5	5.434	10	-3.228					10	6.700	9	-6.770
2005	10	3.767	6	-3.271					10	8.567	6	-6.523
2006	10	4.033	7	-3.028					10	7.255	19	-7.091
2007	11	3.599	11	-3.728					11	7.076	7	-6.771
2008	19	3.774	18	-4.040					4	6.832	7	-7.373
2009	18	3.817	16	-3.636					19	7.850	17	-6.621
2010	14	3.691	11	-3.343					4	6.069	2	-6.844
2011	17	3.369	16	-3.307	1	4.272	3	-4.247	2	9.209	1	-7.154
2012	11	4.543	10	-3.761	6	4.384	3	-4.389	13	6.588	10	-6.193
2013	7	3.410	10	-3.714	9	4.297	8	-4.542	1	5.619	1	-7.212
2014	5	2.907	2	-3.804	13	4.295	13	-4.193	6	6.936	6	-6.740
2015	4	3.793	5	-4.126	5	3.520	9	-3.626	3	9.392	6	-5.933
Total	199		182		34		36		199		198	

Table 4.6: Extreme Event Yearly Distribution (cont'd)

	WTI				Brent				Sugar			
	5% good days		5% bad days		5% good days		5% bad days		5% good days		5% bad days	
	N	Median	N	Median	N	Median	N	Median	N	Median	N	Median
1994	5	4.690	8	-4.272	4	4.061	8	-4.169	6	4.113	4	-5.347
1995	0	0	1	-6.237	0	0	4	-3.661	3	4.360	11	-5.362
1996	9	5.039	11	-5.116	15	3.747	12	-4.173	3	3.856	5	-7.101
1997	5	3.778	7	-3.910	3	4.089	7	-3.978	1	4.550	2	-4.181
1998	13	4.696	17	-4.686	14	4.688	20	-4.070	8	4.342	10	-4.214
1999	12	4.538	9	-4.751	16	3.916	10	-4.280	15	4.096	16	-4.960
2000	18	4.195	13	-5.048	16	3.753	17	-5.259	17	4.163	10	-4.960
2001	13	4.310	11	-4.997	13	4.027	9	-5.053	5	3.770	8	-4.698
2002	14	4.646	10	-4.229	10	4.260	12	-4.308	8	4.660	13	-4.763
2003	15	4.362	9	-5.219	13	4.408	10	-4.645	3	3.798	12	-4.355
2004	13	4.385	11	-4.374	19	4.119	13	-3.999	8	4.601	4	-4.766
2005	12	4.033	7	-4.040	14	3.946	4	-4.048	5	4.879	0	0
2006	5	3.840	5	-3.927	3	3.593	2	-4.043	11	3.871	14	-3.706
2007	8	4.615	5	-4.405	6	4.000	6	-3.973	7	3.828	4	-4.620
2008	14	4.295	17	-4.620	16	4.075	16	-5.276	18	4.393	20	-4.354
2009	18	4.736	15	-4.535	22	4.325	11	-4.594	22	4.386	11	-3.736
2010	3	3.811	6	-4.164	5	3.956	4	-3.828	22	4.293	15	-5.970
2011	8	4.281	11	-5.613	5	4.281	9	-4.637	16	4.405	13	-4.118
2012	4	4.674	4	-4.265	4	4.162	4	-3.828	7	4.264	10	-3.574
2013	0	0	0	0	0	0	1	-3.813	0	0	1	-3.539
2014	0	0	4	-4.474	1	3.498	4	-4.343	7	4.044	4	-3.750
2015	12	4.945	18	-4.831	14	4.807	15	-4.636	8	4.493	9	-4.286
Total	201		199		213		200		200		196	

substantial non-zero cumulative returns before the event day may suggest information leakage before the official announcement of the event. However, in this study, the event is not an identifiable action but rather chosen event according to some particular criteria. Any irregular pattern can suggest the pre-event cross market condition or environment that precede the extreme return or the lead-lag relationship in the tails.

3. Behavior in post-event cumulative return can mainly be categorized into three patterns: reverse, continuation or discontinuation. Reverse is a sign of overreaction with correction. Continuation may reflect underreaction or positive feedback trading, while discontinuation suggests the market is efficient in absorbing the shock with a full and timely reaction and no profitable prediction could be made.
4. The three points mentioned above focusing on the interpretation of one particular average cumulative return series. However, one can also look for asymmetry in these series. For example, good day verse bad day asymmetry can suggest the non-unique explanation for information transmission or price pressure. The same return series could behave systematically differently to positive and negative extreme returns in another series, while the traditional time series methods treat the signs of the movement symmetric. Besides, with the same two series under study, systematic responses can be either unidirectional or bidirectional.

There are six series under study and thus 30 pairs with 120 average cumulative return series for good days and bad days. Four plots are arranged together from any pair for better comparison. A general result is that any two series are positively linked, which means positive (negative) cumulative returns are more likely to occur in the good (bad) days of the other if there exists a visible pattern. Additionally, the cumulative returns clustered and unclustered events do not deviate from each other to a large extent in most of the cases.

Brent and Corn Mean returns for Brent are 5% and −5% on good and bad days and 4% and −4% for corn. For pre-event returns, only corn price

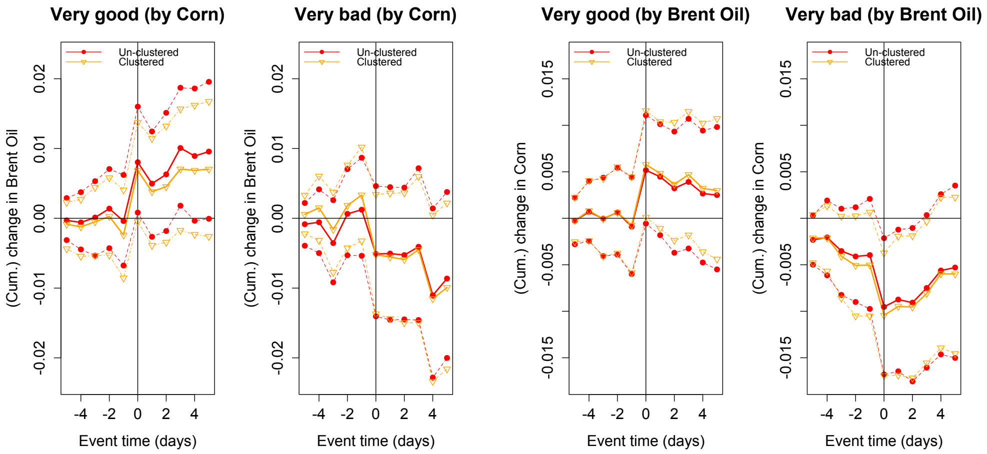

Figure 4.5: Extreme Event and Response between Brent and Corn

has notable decrease leading up to a significant cumulative negative change of corn on the bad day of Brent oil as shown in the fourth plot in Figure 4.5. In other three cases, there seems to be no unusual patterns leading up to the event day. Corn in good and bad days on Brent oil experiences a reverse right after the event with mean estimate from -1% to -0.5% in 5 trading days for bad days. The returns of Brent oil after extreme positive and negative returns on corn continue with the trends in general. Post-event positive and negative feedback trading exists in Brent oil and corn respectively.

Brent and Ethanol Ethanol has mean returns 4% and -5% in the extreme good and bad days. Except in good days defined by ethanol, all the extreme returns are preceded by increasing or decreasing prices of the other series in the pair and are continuing with the trend in the following days. This pattern suggests the extreme negative returns in ethanol are usually accompanied by the bear market in Brent oil while extreme good (bad) days in Brent oil are associated with the bull (bear) market in ethanol. However, Brent oil seems only react to extreme positive return on the event day but no visible pre-event or post-event reaction in ethanol.

Brent and Gas Natural gas, as the most volatile commodity in this study, has 8% and -7% mean return for the extreme event days. Unlike ethanol which is one type of biofuel derived from sugarcane or corn, natural gas is

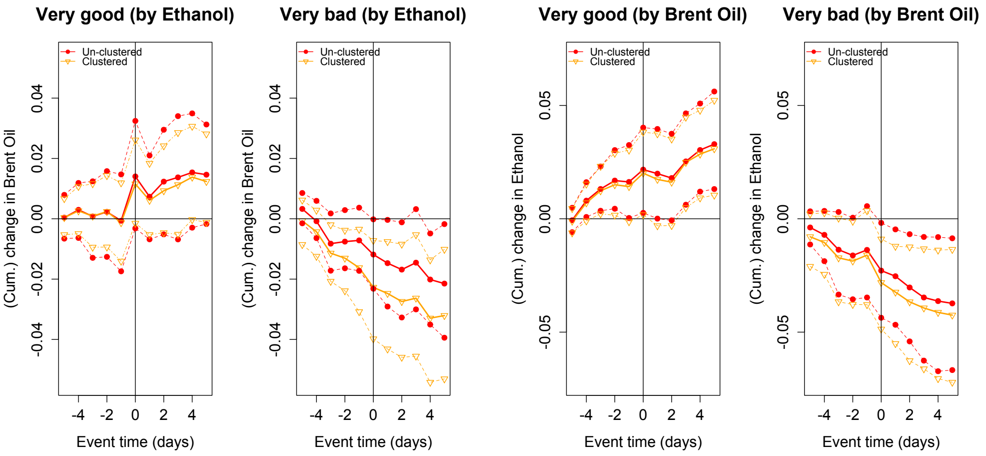

Figure 4.6: Extreme Event and Response between Brent and Ethanol

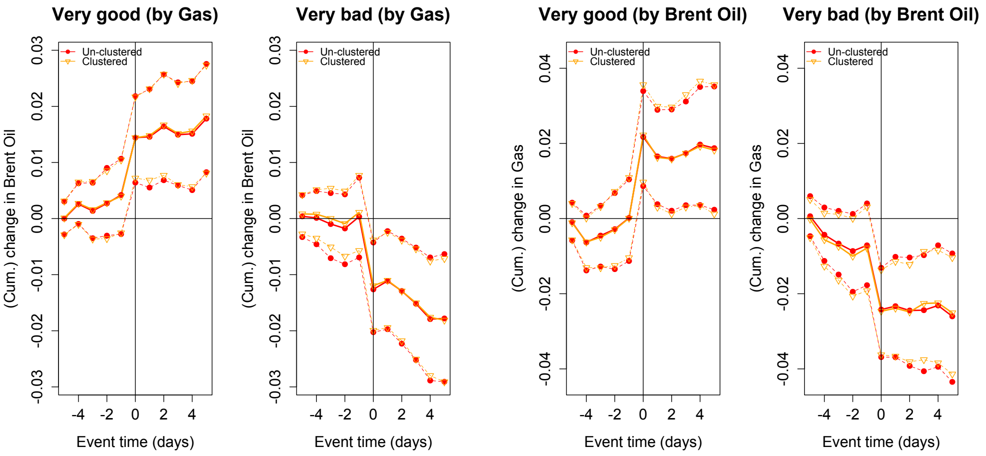

Figure 4.7: Extreme Event and Response between Brent and Gas

more akin to crude oil as fossil fuel. There are visible impacts or changes in Brent oil and natural gas returns on the event days for both series. While the post-event cumulative return of gas simply levels off after extreme days by Brent oil, the Brent oil seems to follow the trend to some extent.

Brent and Sugar The most distinct pattern between Brent oil and sugar is the over-reaction with correction of Brent oil to the good days by sugar. The good days in sugar have mean return 5%. Without any unusual price movement prior to the event, Brent oil on average increase by 1% in those

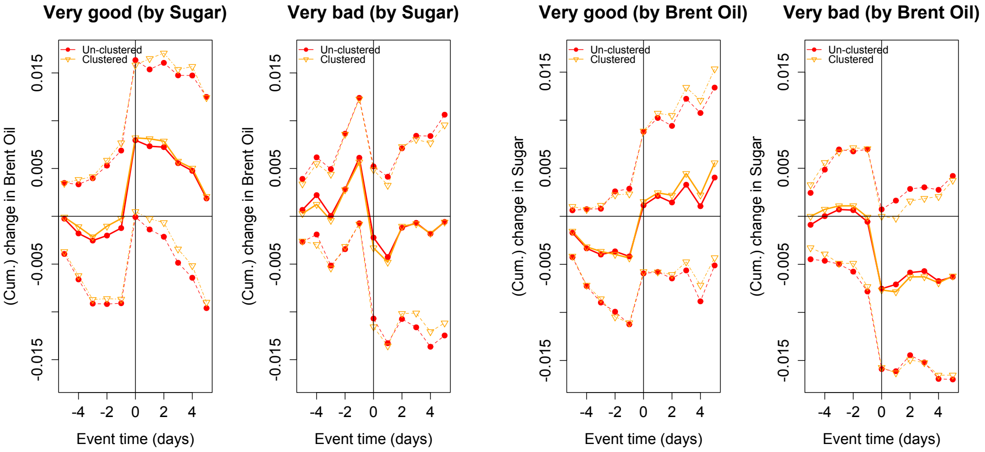

Figure 4.8: Extreme Event and Response between Brent and Sugar

good days and the increase is reversed and disappear in 5 trading days. Sugar tends to have an efficient response to the bad days by Brent oil, which is evidenced by the flat profile after the bad days in Brent oil market. The others two plots in Figure 4.8 do not yield strong evidence on the link between the tail events of Brent oil and sugar.

Brent and WTI Given the cointegration relationship between Brent oil and WTI oil or the stationarity of their spread, the pattern shown in Figure 4.9 is well expected. Before any extreme returns, both markets display tranquility on average as indicated by the flat cumulative return series prior to time 0. On the event days, both series respond with a sharp change cumulative return. After the event days, the return neither continues with the trend nor reverses. This suggests the market within crude oil market is connected in an efficient way in the tail, and no arbitrage argument makes any shocks disappear immediately.

This study also pairs up WTI crude oil with corn, ethanol, and natural gas as a robust check. Figure 4.10, Figure 4.11, Figure 4.12 and Figure 4.13 for WTI oil share the similar patterns to their counterparts with Brent oil.

Corn and Ethanol Corn is an input of ethanol production, and thus theoretically any extreme shocks should have cross-series impact. Prior to any good or bad event days in both series, the market do not show any

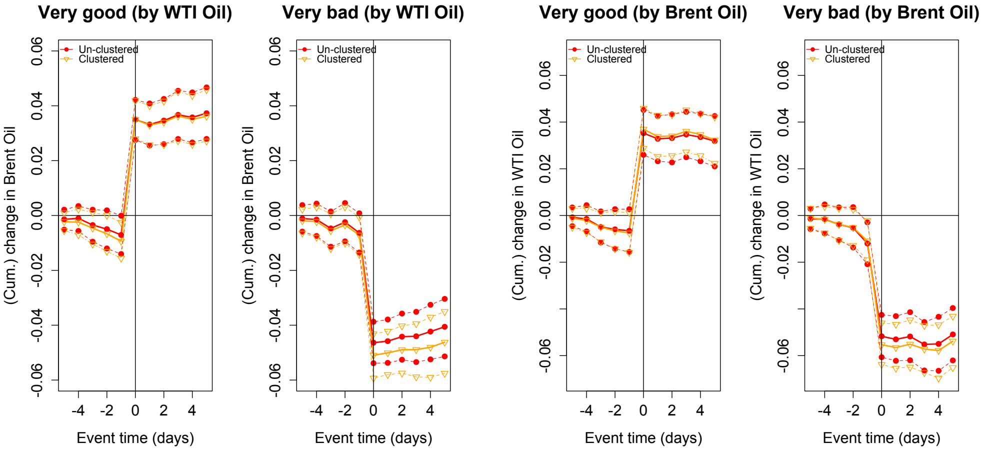

Figure 4.9: Extreme Event and Response between Brent and WTI

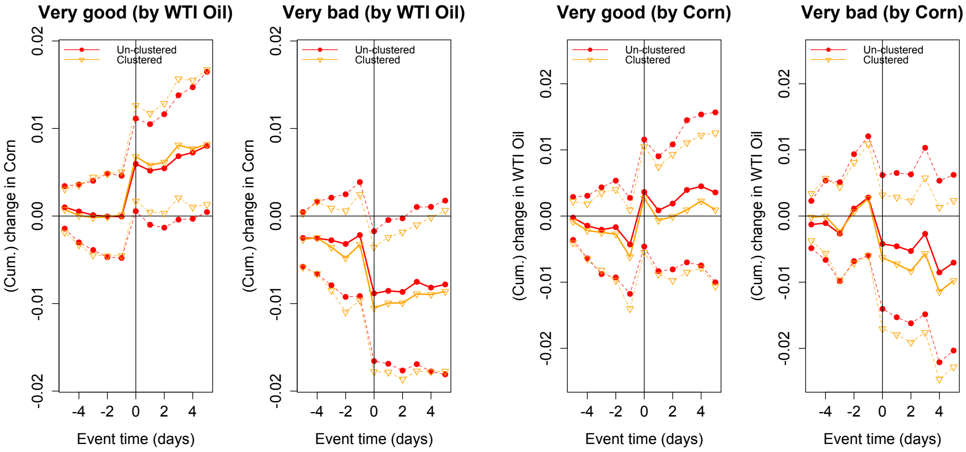

Figure 4.10: Extreme Event and Response between Corn and WTI

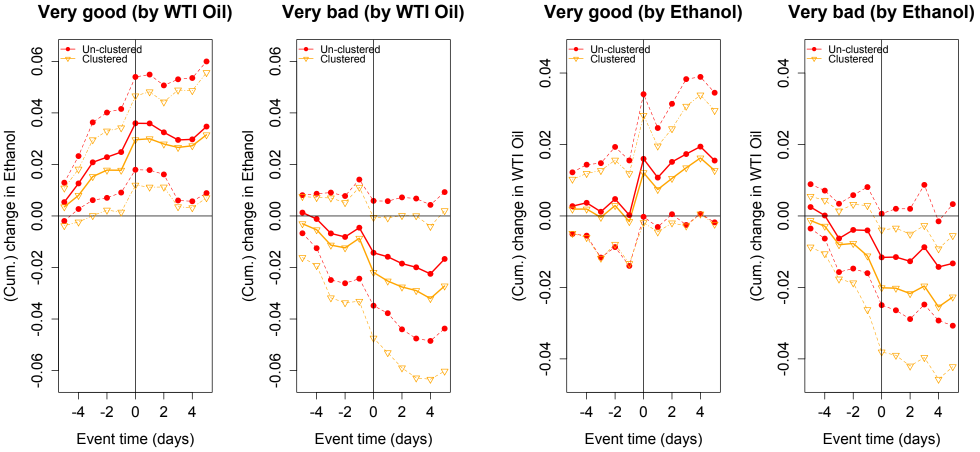

Figure 4.11: Extreme Event and Response between Ethanol and WTI

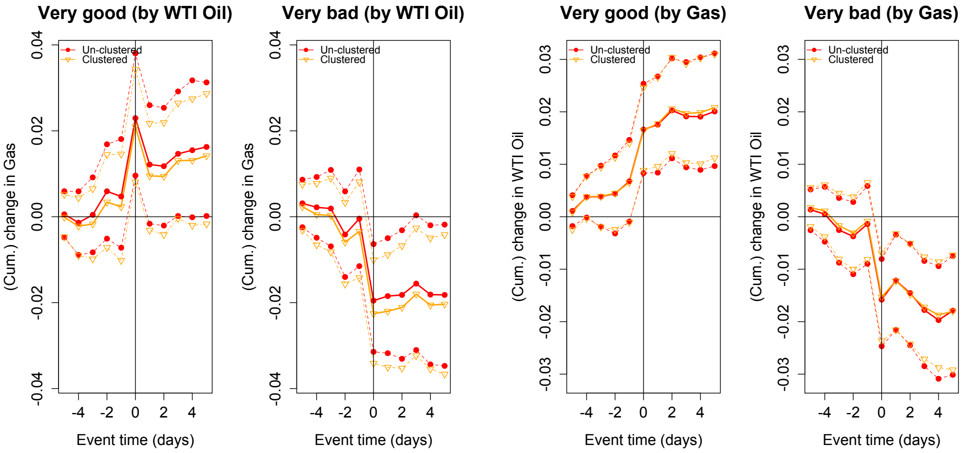

Figure 4.12: Extreme Event and Response between Gas and WTI

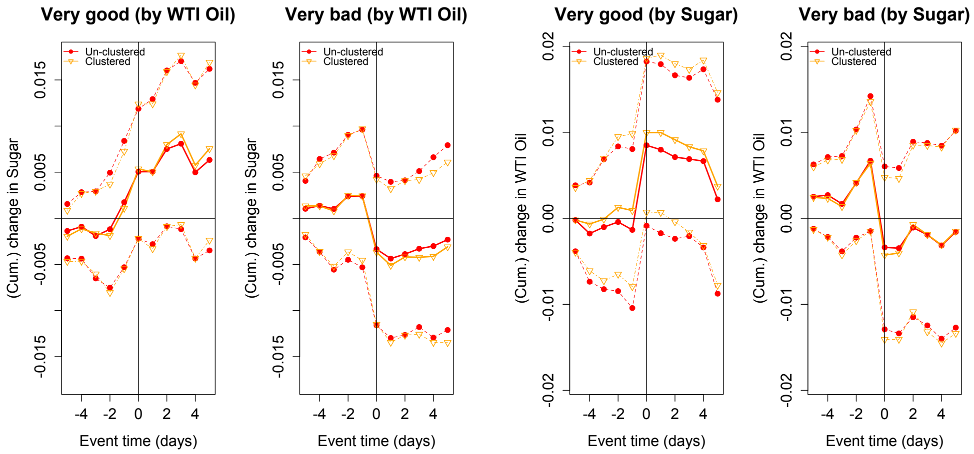

Figure 4.13: Extreme Event and Response between Sugar and WTI

unusual behavior, which suggests the shock is on average surprising, and the extreme shock is unlikely caused by the stressed market conditions in other series. It turns out except for unclustered bad event defined by corn, all cumulative returns become statistically significant on the event days. Focusing on the asymmetry in the impact, one can also notice the impact from the good days have a larger magnitude than that of the bad days even though the quantile table of the extreme events for both series shows bad days with more extreme returns regarding magnitude.

Corn and Gas Corn is responding to the right tail events of natural gas but not to left tail events. Five treading days prior to the extremely positive return on natural gas, the corn has been on an upward trend and jump to a significant cumulative return on the event day. However, this pattern is corrected right after the second day following an average event. The response of natural gas to good days by corn seems noisy and the response to bad days by corn is not significant in spite of a downward trend.

Corn and Sugar Corn and sugar are two soft commodities, which are grown rather than mined. Their responses to cross series extreme day are mainly visible on good days but not bad days. Without any notable cumulative return, corn cumulative return increases by 1% on average good

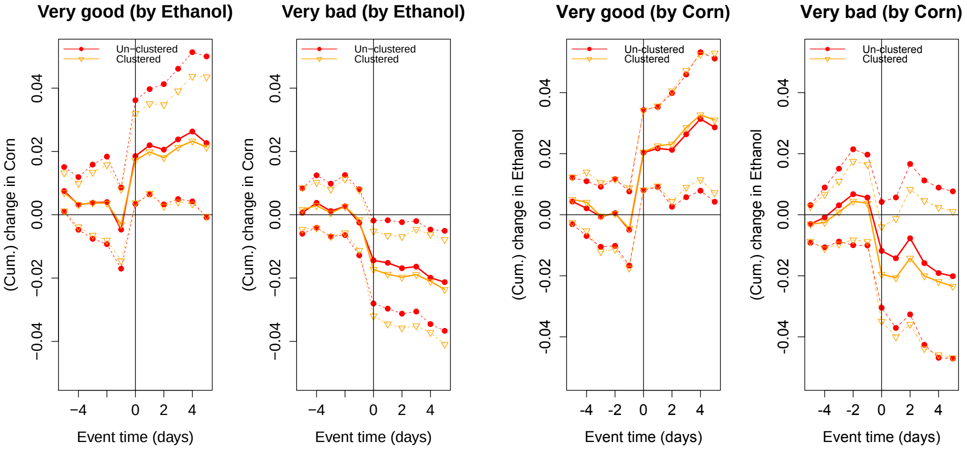

Figure 4.14: Extreme Event and Response between Corn and Ethanol

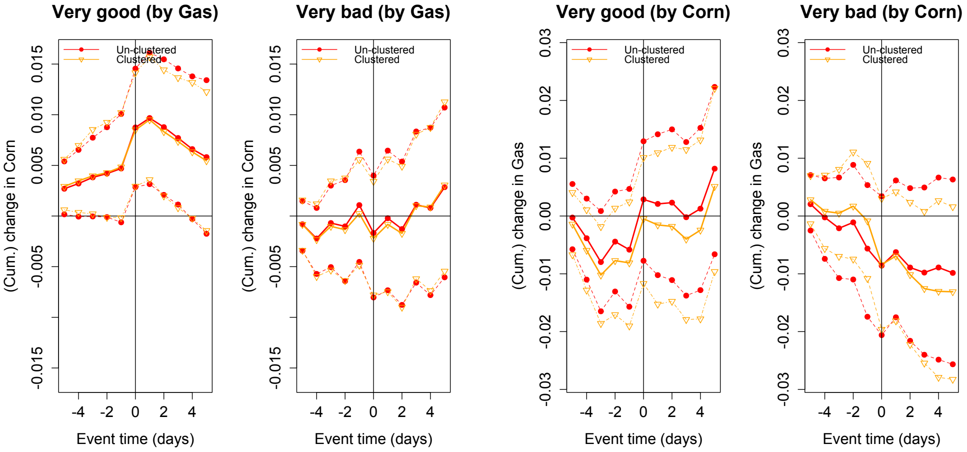

Figure 4.15: Extreme Event and Response between Corn and Gas

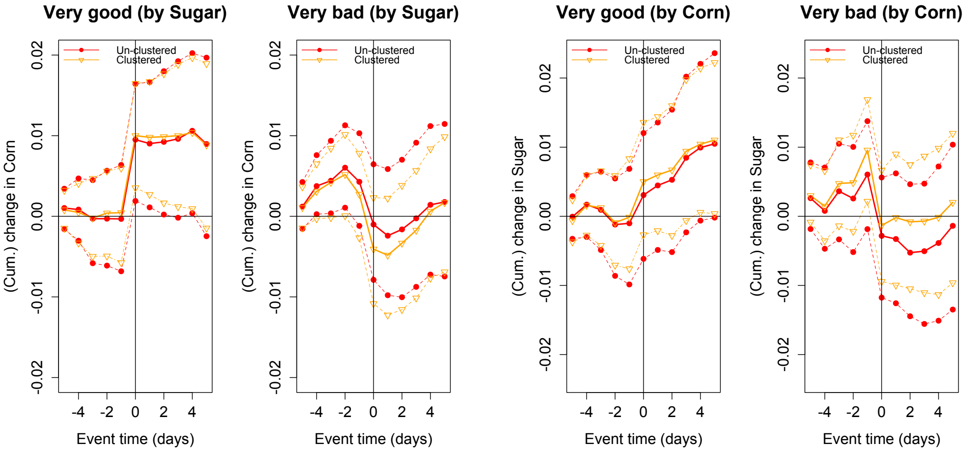

Figure 4.16: Extreme Event and Response between Corn and Sugar

day defined by sugar and maintain at the same level. However, extremely positive returns of corn takes roughly five trading days after event day to achieve the impact of the same magnitude on sugar. For the bad days in both markets, the cumulative returns fluctuate around 0 along the window and are barely significant.

Ethanol and Gas Ethanol seems not to be responsive to the bad days by natural gas as the returns wander around 0 with two diverging confidence bands. The other three plots suggest the extremely positive and negative returns are usually associated with the bull and bear markets of the other series receptively, but the extreme events themselves do not exert any notable impact onto the other market on the event days.

Ethanol and Sugar There is no sign of significant cumulative returns of ethanol prior to any good or bad events by sugar. On the event day, the point estimate of the return is relatively small compared to the cumulative returns realized in a week after the event days. The plot suggests on average there might be a time lag of two days for an extremely negative return in sugar to have an impact on ethanol. As for the sugar, response associated with good days in ethanol does not deviate from 0 in magnitude and is not significant along the event window. The downward trend in the sugar seems

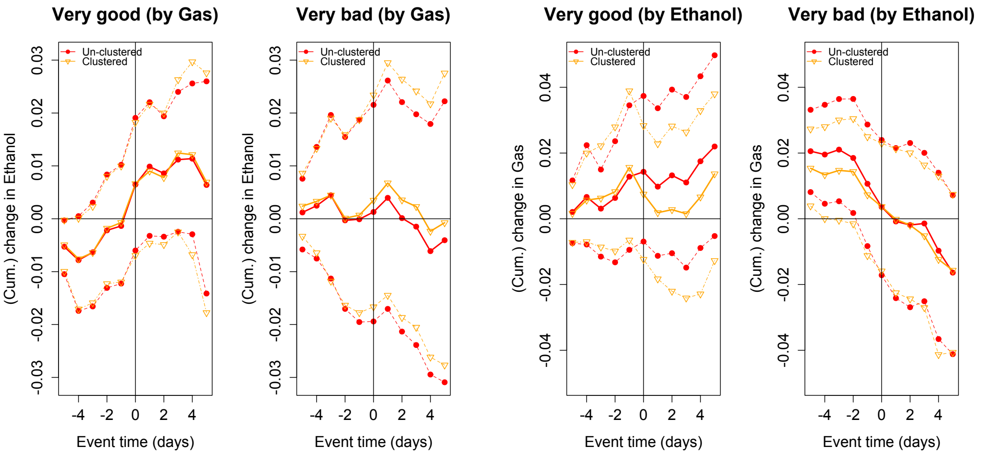

Figure 4.17: Extreme Event and Response between Ethanol and Gas

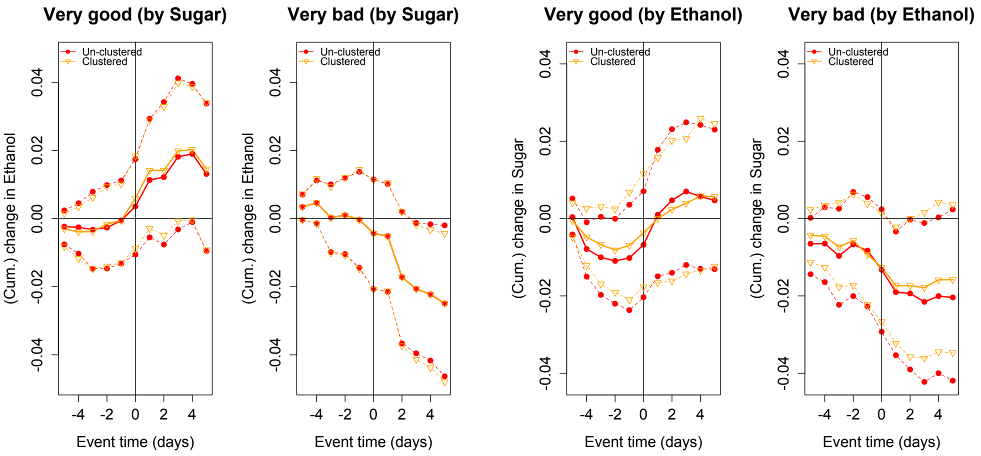

Figure 4.18: Extreme Event and Response between Ethanol and Sugar

to precede the bad days in ethanol despite its statistical insignificance.

Gas and Sugar Natural gas experiences bull market five days before the positive events of sugar with statistical significance and the trend is somewhat reversed with correction. For the bad day of sugar, natural gas does not signal any coming extreme negative shock in sugar until two days prior to the events and the trend is sustained and continued. The other side of the interaction shows a similar pattern but in a less convincing way as the confidence interval get wider.

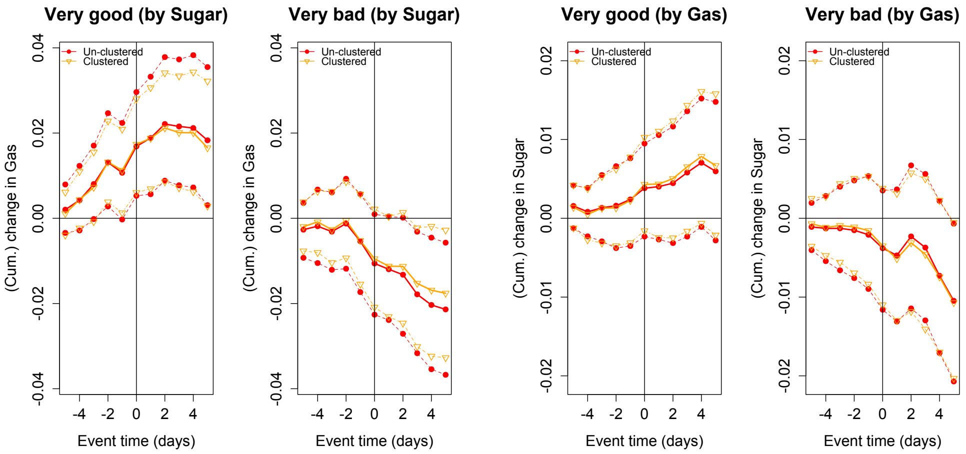

Figure 4.19: Extreme Event and Response between Gas and Sugar

4.4.4 Discussion on the Economic Story

The methodology employed in this section is novel. Although it does not establish causal relation among the commodity extreme event and cross responses, it demonstrates the interactions among the impact of extreme returns across commodities. In summary, the response around the extreme return could be categorized as trend and reversal of initial rend or trend continuation. The economic theory and rationale behind these empirical are both rational and behavioral. It is also related to some strand of literature in behavioral finance and market microstructure. Pedersen (2015) provides a good source of review. Initial underreaction to information happens when shocks, in our case, extreme returns across commodities cause the value of an asset change immediately. market price follows the direction of change but its initial underreaction results in subsequent trend. Literature has documented the causes for this initial underreaction (Barberis, Shleifer, and Vishny, 1998; Duffie, 2010; Frazzini, 2006)

1. Anchor and insufficient adjustment: human tend to rely heavily on the first pieces of information and adjust the view insufficiently to the new information.

2. The disposition effect: People tend to realize gain early and loss later.

This creates counter price trend pressures and slow down the adjustment to new information.

3. Non profit seeking activities (especially in fixed income and foreign exchange market): central bank interference market to reduce the volatility of the exchange rate and interest rate, potentially slowing down the adjustment process.
4. Frictions and slow moving capital: some market participant is constrained by regulations and market frictions and this results in delayed response to new information and thus initial underreaction.

Following the initial trend, the trend can either continue even beyond the fundamental value or reverse. Trend continuations can be explained by delayed overreaction (Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; Vayanos and Woolley, 2013; Welch, 2000).

1. Herding and feedback trading: when initial trend starts, some traders may begins to pariticipate due to herding and feedback trading.
2. Confirmation bias and representativeness: Human tend to focus too much on evidence that confirms what they already believe and ignore others. The recent price trend is perceived as the representative of the future thus inducing capital flowing from losers to winner of asset and continuing the trend.

The findings that some of the seemingly unrelated commodities response to extreme events of one another could be puzzling. This can be explained by the increasingly important direct and indirect participation of hedge fund and Commodity Trading Advisor (CTA) in the commodities market. When market participants suffer from extreme loss, they may rebalance the portfolio positions due to risk management scheme, regulations, client contribution withdrawals.

4.5 Conclusion

Whether or not and how commodities are connected is a general question many researchers focus on and try to answer either from a theoretical perspective or an empirical perspective. Both linear and nonlinear techniques have been applied to this question. However, whether the tail event interaction of commodities behave differently or whether the tail dynamics respond asymmetrically to positive and negative extreme events defined by the other commodities are questions that may not be easily answered with traditional time series methodology unless it is explicitly modeled. Answering this question or even the attempt to document stylized facts on this question will enhance our understanding of commodity dynamics.

This chapter utilizes the modified event study method which focuses on the daily extreme returns of every commodity future settlement prices and tracks the cumulative return pattern around the extreme return dates of other commodities. The statistical inference procedure applies bootstrapping method without parametric distributional assumption. Point estimate of the average cumulative return can reflect how the commodity market is linked in the tail given the pattern and the associated standard deviation. The well-documented interpretation of traditional event study methodology is borrowed. It finds out that the interaction of tail dynamics of commodity returns is complex regarding tail asymmetry, pre-event and post-event market efficiency and information flows direction. Magnitude asymmetry exists in the of the responses to the positive and negative event days. Directional asymmetry also exists, which means the responses between extreme returns of two commodities could be unidirectional or bi-directional. Generalized impulse response function is conducted with a VAR model for comparison and reveals that there is distinct pattern of the extreme returns response.

For future study, a closer look at these event days could be carried out in details. First, the classification of different patterns should be examined for underlying transmission mechanism. Whether the pattern is due to market condition, any behavioral biases, or economics equilibrium forces are worth examining. Second, non-price series can be included in the analysis. Trading volumes and open interests capture the trading activities, and the determination of holding long/short position by market participants, and thus tail event analysis can provide a unique perspective.

Chapter 5

Conclusion

The increased complexity of commodity interaction and dynamics driven by both commodity financialization and the nature of the commodity products motivates this thesis to devote into volatility modeling, nonlinear linkage and extreme return interaction in three self-contained essays.

The first essay points out the missing gap in agricultural commodity volatility modeling. There is strong empirical evidence showing the volatility persistence in agricultural commodity which most conditional volatility models fail to capture. However, limited attention has been paid to this stylized fact despite the importance of volatility modeling in volatility trading, derivative pricing and portfolio optimization besides theoretical interest. The first essay studies the long-run dependence in return volatility of corn, rice, soybean, and wheat with daily return from Jan 3^{rd}, 1994 to Feb 18^{th}, 2015. It compares the modeling performance within the sample and out of forecast measure of both standard GARCH model and component GARCH model with normal, student, (skewed) generalized error distribution. It finds out strong evidence on long run and short run component structure with component GARCH model in most of the cases. For conditional distribution, although skewness introduced by inverse scale factors are found to be highly significant, out of sample performance favors conditional distribution without skewness. This may due to estimation error and it suggests that skewness is of less importance than fat-tailness for agricultural commodity modeling. However, the volatility persistence turns out to be essential due to the superiority of out of sample forecasting by component GARCH model as evidenced by Diebold-Mariano test on one day ahead forecast. Besides, VaR forecast is backtested with unconditional coverage and conditional coverage test and the results again favor the component GARCH over standard GARCH model.

The dynamics of grain products has been well explained by Marshallian model of demand and supply with inter-grain substitution (substitution of one grain for another) and inter-temporal substitution (storage enables substitution of current consumption for future consumption) until 2004. Biofuel production surge is pointed out in the literature to explain it. Biofuel production surge has also stimulated both theoretical and empirical studies on the energy and grain linkage. However, the empirical findings regarding the linkage is mixed. Since literature on time series has pointed out unit roots and cointegration tests have low power to detect unit roots or cointegration in the presence of asymmetric adjustment, the failure of some of the existing literature to detect cointegration may be due to this misspecification. Thus the second essay applies a non-linear cointegration with asymmetric adjustment threshold and its error correction model to study the global energy and grain linkage. It finds out global energy price index and global grain index are cointegrated with energy price evolving more independently than grain price. This is consistent with the notion that energy price is mainly driven by its fundamentals such as supply and demand while agricultural commodity could also be affected by derived demand such as production of biofuel. Asymmetry is also found in both long run and short run. In the long run, disequilibrium adjustment responds asymmetrically to previous positive or negative deviation in the MTAR cointegration while in the short run the asymmetry exists only in error correction adjustment for the grain series.

The literature on the interaction between commodities does not single out the extreme price changes from the normal returns. The third essay on cross-commodity extreme event finds out there are distinct and mixed patterns in the extreme returns compared to those suggested by traditional time series methods. For traditional time series methods, this essay computes generalized impulse response function from a VAR model and finds out the impacts of shocks become negligible within two to three trading days. However, it utilizes the modified event study method to track the cumulative return response of Brent oil, corn, ethanol, natural gas, sugar and WTI oil around extreme return days defined by these commodities and finds out cumulative return response exhibits noticeable and distinct patterns after the extreme shocks. It also examines whether there is heterogeneity in the interaction between extreme returns. Bootstrapping method is applied for statistical inference without parametric distributional assumption. It finds out the interaction of tail dynamics of commodity returns is complex regarding asymmetry, pre-event and post-event market response and information flow direction. These findings suggest treating all the return shocks homogeneous might be misleading.

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Appendix A

Appendix

Table A.1: GARCH-normal estimation result for Corn

	garch11normal	garch12normal	garch21normal	garch22normal
omega	.04797	.05106	.04802	.05106
	(.02948)	(.02828)	(.03537)	(.03699)
alpha1	.08679*	.09231**	.08680*	.09230*
	(.03436)	(.03163)	(.03934)	(.04347)
beta1	.90260***	.82189***	.90256***	.82194***
	(.03890)	(.06955)	(.05107)	(.11356)
beta2		.07442		.07437
		(.08120)		(.06788)
alpha2			.00000	.00000
			(.06265)	(.07036)
AIC	3.74880	3.74941	3.74946	3.74993
BIC	3.75371	3.75596	3.75601	3.75812
SIC	3.74880	3.74941	3.74946	3.74993
HQIC	3.75055	3.75174	3.75179	3.75284

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.2: GARCH-student estimation result for Corn

	garch11student	garch12student	garch21student	garch22student
omega	.05549*	.05554**	.05660*	.09315*
	(.02224)	(.02151)	(.02444)	(.03731)
alpha1	.10387***	.10396***	.09819**	.08459**
	(.01921)	(.01832)	(.03061)	(.02682)
beta1	.88464***	.88456***	.88265***	.24075*
	(.02342)	(.10826)	(.02840)	(.11482)
shape	5.13805***	5.13347***	5.13496***	5.13941***
	(.45432)	(.45423)	(.45589)	(.45672)
beta2		.00002		.56475***
		(.10394)		(.10925)
alpha2			.00752	.09105**
			(.03855)	(.03125)
AIC	3.65089	3.65148	3.65147	3.65170
BIC	3.65744	3.65967	3.65965	3.66152
SIC	3.65089	3.65148	3.65147	3.65169
HQIC	3.65322	3.65439	3.65438	3.65519

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.3: GARCH-ged estimation result for Corn

	garch11ged	garch12ged	garch21ged	garch22ged
omega	.05267*	.05275*	.05392	.08550*
	(.02437)	(.02328)	(.02924)	(.03909)
alpha1	.09575***	.09582***	.09069**	.08060**
	(.02404)	(.02174)	(.03169)	(.02977)
beta1	.89133***	.89124***	.88916***	.31110
	(.02905)	(.06635)	(.03850)	(.16634)
shape	1.22473***	1.22450***	1.22435***	1.22434***
	(.05562)	(.05559)	(.05559)	(.05582)
beta2		.00000		.51228**
		(.07165)		(.16878)
alpha2			.00699	.07539*
			(.04538)	(.03490)
AIC	3.66408	3.66469	3.66468	3.66503
BIC	3.67063	3.67288	3.67286	3.67485
SIC	3.66408	3.66469	3.66467	3.66502
HQIC	3.66641	3.66760	3.66759	3.66852

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.4: GARCH-sged estimation result for Corn

	garch11sged	garch12sged	garch21sged	garch22sged
omega	.04864*	.04871*	.04944	.07967
	(.02197)	(.02122)	(.02681)	(.04374)
alpha1	.09239***	.09245***	.08870*	.07704**
	(.02227)	(.01983)	(.03773)	(.02929)
beta1	.89556***	.89542***	.89413***	.29785
	(.02668)	(.04765)	(.03618)	(.72077)
skew	1.04685***	1.04685***	1.04678***	1.04679***
	(.01816)	(.01816)	(.01828)	(.01829)
shape	1.23582***	1.23561***	1.23548***	1.23548***
	(.05501)	(.05496)	(.05500)	(.05538)
beta2		.00005		.53080
		(.06294)		(.65915)
alpha2			.00495	.07489
			(.05188)	(.06206)
AIC	3.66354	3.66414	3.66414	3.66447
BIC	3.67172	3.67397	3.67396	3.67593
SIC	3.66354	3.66414	3.66413	3.66446
HQIC	3.66645	3.66763	3.66763	3.66854

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.5: Component GARCH-normal estimation result for Corn

	csGARCH11nor	csGARCH12nor	csGARCH21nor	csGARCH22nor
omega	.04121***	.04127***	.04160***	.04144***
	(.01040)	(.00664)	(.01061)	(.01059)
alpha1	.05614***	.05614*	.02608	.02587
	(.01654)	(.02472)	(.03695)	(.03828)
beta1	.81988***	.81977	.77969***	.67459***
	(.04569)	(.75328)	(.08349)	(.00850)
eta11	.98929***	.98918***	.98930***	.98933***
	(.00018)	(.00000)	(.00006)	(.00000)
eta21	.06817***	.06792***	.06917***	.06904***
	(.01896)	(.01866)	(.01941)	(.01952)
beta2		.00000		.08690
		(.66414)		(.07996)
alpha2			.04473*	.05072
			(.02075)	(.03782)
AIC	3.74572	3.74652	3.74567	3.74618
BIC	3.75390	3.75634	3.75549	3.75764
SIC	3.74572	3.74651	3.74567	3.74618
HQIC	3.74863	3.75001	3.74916	3.75026

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.6: Component GARCH-student estimation result for Corn

	csGARCH11student	csGARCH12student	csGARCH21student	csGARCH22student
omega	.05298	.05327***	.05253***	.01724***
	(.04432)	(.01282)	(.01219)	(.00430)
alpha1	.01211	.01184	.00188	.07557**
	(.04066)	(.02053)	(.03214)	(.02412)
beta1	.85662***	.85487***	.84663***	.24451***
	(.15441)	(.15278)	(.12479)	(.01724)
eta11	.98630***	.98597***	.98623***	.99536***
	(.01119)	(.00358)	(.00280)	(.00000)
eta21	.09389*	.09377***	.09312***	.00775***
	(.04040)	(.02006)	(.01897)	(.00153)
shape	5.27327***	5.28113***	5.29132***	5.30542***
	(.49256)	(.45806)	(.46391)	(.45978)
beta2		.00007		.56331***
		(.05240)		(.01206)
alpha2			.01344	.08536**
			(.03013)	(.02710)
AIC	3.65247	3.65316	3.65309	3.65396
BIC	3.66229	3.66462	3.66455	3.66705
SIC	3.65246	3.65316	3.65309	3.65395
HQIC	3.65596	3.65724	3.65717	3.65861

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.7: Component GARCH-ged estimation result for Corn

	csGARCH11ged	csGARCH12ged	csGARCH21ged	csGARCH22ged
omega	.04532***	.04545***	.04514***	.04466***
	(.00871)	(.00898)	(.00914)	(.00889)
alpha1	.02994	.02990	.00977	.00729
	(.03972)	(.01560)	(.03220)	(.03139)
beta1	.85183***	.85131**	.83192***	.35318
	(.09130)	(.31745)	(.07513)	(.24465)
eta11	.98719***	.98701***	.98725***	.98739***
	(.00453)	(.00001)	(.00098)	(.00112)
eta21	.07901*	.07880***	.07910***	.07883***
	(.03251)	(.01750)	(.01685)	(.01826)
shape	1.23492***	1.23490***	1.23613***	1.23597***
	(.05542)	(.05381)	(.05451)	(.05442)
beta2		.00001		.40707*
		(.29094)		(.19214)
alpha2			.02643	.04377
			(.03283)	(.03072)
AIC	3.66484	3.66553	3.66530	3.66568
BIC	3.67466	3.67699	3.67676	3.67877
SIC	3.66483	3.66553	3.66529	3.66567
HQIC	3.66833	3.66961	3.66937	3.67033

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.8: Component GARCH-sged estimation result for Corn

	csGARCH11sged	csGARCH12sged	csGARCH21sged	csGARCH22sged
omega	.04257***	.04269***	.04240***	.04191***
	(.00173)	(.00851)	(.00855)	(.00851)
alpha1	.02953	.02948	.00920	.00637
	(.01909)	(.01912)	(.01378)	(.02846)
beta1	.84973***	.84929***	.82892***	.33415
	(.04966)	(.02413)	(.07209)	(.22526)
eta11	.98784***	.98767***	.98790***	.98803***
	(.00001)	(.00002)	(.00001)	(.00032)
eta21	.07744***	.07723***	.07756***	.07728***
	(.01295)	(.01609)	(.01583)	(.01544)
skew	1.04624***	1.04628***	1.04584***	1.04632***
	(.01843)	(.01857)	(.01894)	(.01863)
shape	1.24574***	1.24572***	1.24701***	1.24698***
	(.05170)	(.05299)	(.05341)	(.05343)
beta2		.00000		.41929*
		(.04354)		(.18153)
alpha2			.02679	.04479
			(.02692)	(.02722)
AIC	3.66425	3.66495	3.66470	3.66506
BIC	3.67571	3.67805	3.67780	3.67979
SIC	3.66425	3.66494	3.66469	3.66505
HQIC	3.66833	3.66960	3.66936	3.67029

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.9: GARCH-normal estimation result for Rice

	garch11normal	garch12normal	garch21normal	garch22normal
omega	.05069*	.06641*	.05072*	.06641**
	(.02285)	(.03336)	(.02075)	(.02568)
alpha1	.09079***	.12129***	.09083*	.12130**
	(.01535)	(.02454)	(.04145)	(.04555)
beta1	.90610***	.52531*	.90606***	.52513**
	(.01482)	(.23780)	(.01382)	(.16487)
beta2		.34966		.34983*
		(.21417)		(.15245)
alpha2			.00000	.00000
			(.04913)	(.05994)
AIC	3.91390	3.91371	3.91440	3.91423
BIC	3.91880	3.92025	3.92095	3.92241
SIC	3.91390	3.91371	3.91440	3.91423
HQIC	3.91564	3.91603	3.91673	3.91714

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.10: GARCH-student estimation result for Rice

	garch11student	garch12student	garch21student	garch22student
omega	.05685*	.08056**	.05682*	.08056
	(.02401)	(.03041)	(.02684)	(.05376)
alpha1	.07340***	.10580***	.07340**	.10580**
	(.02031)	(.02472)	(.02361)	(.03848)
beta1	.91263***	.43525***	.91263***	.43524
	(.02334)	(.11990)	(.02852)	(.54232)
shape	4.45891***	4.48600***	4.45906***	4.48583***
	(.37469)	(.37827)	(.37455)	(.37669)
beta2		.43915***		.43915
		(.11053)		(.47210)
alpha2			.00000	.00000
			(.03073)	(.09034)
AIC	3.73580	3.73508	3.73628	3.73560
BIC	3.74234	3.74326	3.74446	3.74542
SIC	3.73580	3.73508	3.73628	3.73560
HQIC	3.73812	3.73799	3.73919	3.73909

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.11: GARCH-ged estimation result for Rice

	garch11ged	garch12ged	garch21ged	garch22ged
omega	.05853**	.08046**	.05853*	.08045*
	(.02260)	(.02988)	(.02332)	(.03811)
alpha1	.07627***	.10687***	.07627**	.10688**
	(.01649)	(.02213)	(.02644)	(.03590)
beta1	.90889***	.46403***	.90888***	.46403
	(.01985)	(.12292)	(.02179)	(.32416)
shape	1.12218***	1.12360***	1.12218***	1.12360***
	(.06518)	(.06589)	(.06573)	(.06606)
beta2		.40884***		.40883
		(.11201)		(.28342)
alpha2			.00000	.00000
			(.03002)	(.06365)
AIC	3.75741	3.75700	3.75791	3.75752
BIC	3.76395	3.76518	3.76609	3.76733
SIC	3.75740	3.75699	3.75790	3.75752
HQIC	3.75973	3.75990	3.76081	3.76101

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.12: GARCH-sged estimation result for Rice

	garch11sged	garch12sged	garch21sged	garch22sged
omega	.05851**	.08045**	.05851*	.08042*
	(.02259)	(.02989)	(.02331)	(.03807)
alpha1	.07627***	.10687***	.07627**	.10687**
	(.01649)	(.02213)	(.02644)	(.03589)
beta1	.90890***	.46401***	.90889***	.46401
	(.01985)	(.12290)	(.02179)	(.32392)
skew	1.00019	1.00025	1.00020	1.00025
	(.00262)	(.00265)	(.00262)	(.00265)
shape	1.12235***	1.12382***	1.12236***	1.12383***
	(.06511)	(.06580)	(.06566)	(.06597)
beta2		.40885***		.40886
		(.11198)		(.28321)
alpha2			.00000	.00000
			(.03002)	(.06361)
AIC	3.75793	3.75752	3.75843	3.75804
BIC	3.76611	3.76733	3.76824	3.76949
SIC	3.75793	3.75751	3.75842	3.75804
HQIC	3.76084	3.76101	3.76192	3.76211

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.13: Component GARCH-normal estimation result for Rice

	csGARCH11nor	csGARCH12nor	csGARCH21nor	csGARCH22nor
omega	.05612***	.05627***	.05627***	.05627***
	(.01514)	(.01583)	(.01212)	(.01658)
alpha1	.02520	.02561	.02502	.02561
	(.08443)	(.11624)	(.05683)	(.06859)
beta1	.08530	.00001	.08517	.00001
	(1.51020)	(1.54753)	(1.27045)	(1.01762)
eta11	.99229***	.99214***	.99217***	.99214***
	(.00005)	(.00747)	(.00615)	(.00776)
eta21	.08530***	.08512***	.08516***	.08512***
	(.00631)	(.01410)	(.01210)	(.01480)
beta2		.08511		.08511
		(.43759)		(.18633)
alpha2			.00000	.00000
			(.06299)	(.04430)
AIC	3.91534	3.91604	3.91607	3.91657
BIC	3.92352	3.92586	3.92588	3.92802
SIC	3.91534	3.91604	3.91606	3.91656
HQIC	3.91825	3.91953	3.91956	3.92064

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.14: Component GARCH-student estimation result for Rice

	csGARCH11student	csGARCH12student	csGARCH21student	csGARCH22student
omega	.00621	.00590***	.00619	.00590***
	(.00410)	(.00174)	(.00444)	(.00175)
alpha1	.08780	.11160	.08750*	.11161
	(.04872)	(.07160)	(.04169)	(.06387)
beta1	.85968***	.42854***	.86007***	.42846***
	(.12488)	(.06841)	(.14485)	(.12649)
eta11	.99909***	.99899***	.99905***	.99899***
	(.00000)	(.00000)	(.00000)	(.00001)
eta21	.01778	.01623***	.01745	.01623**
	(.00980)	(.00420)	(.01055)	(.00543)
shape	4.36389***	4.42175***	4.37120***	4.42158***
	(.34951)	(.36216)	(.35172)	(.36731)
beta2		.39967***		.39974***
		(.06751)		(.09578)
alpha2			.00000	.00000
			(.03617)	(.06625)
AIC	3.73422	3.73396	3.73480	3.73448
BIC	3.74404	3.74541	3.74625	3.74757
SIC	3.73422	3.73395	3.73479	3.73447
HQIC	3.73771	3.73803	3.73887	3.73913

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.15: Component GARCH-ged estimation result for Rice

	csGARCH11ged	csGARCH12ged	csGARCH21ged	csGARCH22ged
omega	.04807***	.00537**	.04811*	.04779***
	(.01036)	(.00171)	(.01885)	(.00964)
alpha1	.05323	.10299**	.05240	.06596
	(.03346)	(.03614)	(.03721)	(.03493)
beta1	.66644***	.46327***	.67839	.30452
	(.13711)	(.02571)	(.49808)	(.39585)
eta11	.98805***	.99881***	.98788***	.98795***
	(.00122)	(.00000)	(.00372)	(.00027)
eta21	.06337***	.01327***	.06289***	.06256***
	(.01919)	(.00243)	(.01788)	(.01103)
shape	1.11865***	1.12283***	1.11890***	1.11982***
	(.06453)	(.06478)	(.06561)	(.06560)
beta2		.38577***		.31496
		(.03917)		(.17992)
alpha2			.00000	.00000
			(.04309)	(.04538)
AIC	3.75725	3.75652	3.75778	3.75803
BIC	3.76707	3.76797	3.76923	3.77111
SIC	3.75725	3.75652	3.75778	3.75802
HQIC	3.76074	3.76059	3.76185	3.76268

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.16: Component GARCH-sged estimation result for Rice

	csGARCH11sged	csGARCH12sged	csGARCH21sged	csGARCH22sged
omega	.00530***	.00537**	.00534***	.00537**
	(.00115)	(.00170)	(.00134)	(.00170)
alpha1	.07746***	.10298**	.07720***	.10298**
	(.00177)	(.03923)	(.02079)	(.03497)
beta1	.88506***	.46324***	.88531***	.46323***
	(.00179)	(.03149)	(.00043)	(.04784)
eta11	.99892***	.99881***	.99887***	.99881***
	(.00000)	(.00000)	(.00000)	(.00000)
eta21	.01414***	.01327***	.01385***	.01327***
	(.00082)	(.00245)	(.00175)	(.00260)
skew	1.00014	1.00019	1.00014	1.00018
	(.00261)	(.00262)	(.00261)	(.00262)
shape	1.12043***	1.12299***	1.12070***	1.12298***
	(.06441)	(.06469)	(.06481)	(.06464)
beta2		.38582***		.38583***
		(.03846)		(.04387)
alpha2			.00000	.00000
			(.02474)	(.04175)
AIC	3.75719	3.75704	3.75776	3.75757
BIC	3.76864	3.77013	3.77084	3.77229
SIC	3.75718	3.75704	3.75775	3.75756
HQIC	3.76126	3.76169	3.76241	3.76280

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.17: GARCH-normal estimation result for Soybean

	garch11normal	garch12normal	garch21normal	garch22normal
omega	.02980*	.03917*	.02989*	.03916
	(.01358)	(.01707)	(.01497)	(.02623)
alpha1	.08544***	.11005***	.08559***	.11005***
	(.01532)	(.01991)	(.02447)	(.02781)
beta1	.90822***	.55264***	.90805***	.55263
	(.01556)	(.13509)	(.02131)	(.69716)
beta2		.32836**		.32837
		(.12667)		(.62767)
alpha2			.00000	.00000
			(.03209)	(.08789)
AIC	3.60294	3.60158	3.60354	3.60210
BIC	3.60785	3.60812	3.61008	3.61028
SIC	3.60294	3.60157	3.60354	3.60210
HQIC	3.60468	3.60390	3.60586	3.60501

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.18: GARCH-student estimation result for Soybean

	garch11student	garch12student	garch21student	garch22student
omega	.03372**	.04343**	.03381**	.04343**
	(.01252)	(.01452)	(.01306)	(.01483)
alpha1	.06748***	.08552***	.06757**	.08553***
	(.01192)	(.01267)	(.02188)	(.02528)
beta1	.92090***	.61402***	.92078***	.61394***
	(.01386)	(.04919)	(.01631)	(.04572)
shape	5.74460***	5.78328***	5.74189***	5.78271***
	(.59322)	(.59406)	(.57204)	(.58392)
beta2		.28518***		.28526***
		(.04688)		(.03584)
alpha2			.00000	.00000
			(.02617)	(.03042)
AIC	3.53381	3.53392	3.53442	3.53445
BIC	3.54035	3.54210	3.54260	3.54426
SIC	3.53380	3.53392	3.53442	3.53444
HQIC	3.53613	3.53683	3.53733	3.53793

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.19: GARCH-ged estimation result for Soybean

	garch11ged	garch12ged	garch21ged	garch22ged
omega	.03286**	.04324**	.03295*	.04324
	(.01275)	(.01536)	(.01369)	(.02376)
alpha1	.07382***	.09503***	.07394***	.09503*
	(.01249)	(.01505)	(.02120)	(.03867)
beta1	.91508***	.57256***	.91494***	.57257
	(.01437)	(.10563)	(.01812)	(.38470)
shape	1.33126***	1.33482***	1.33117***	1.33482***
	(.05533)	(.05506)	(.05355)	(.05357)
beta2		.31737**		.31737
		(.09946)		(.33780)
alpha2			.00000	.00000
			(.02676)	(.07642)
AIC	3.54687	3.54658	3.54748	3.54711
BIC	3.55341	3.55476	3.55565	3.55692
SIC	3.54687	3.54658	3.54747	3.54710
HQIC	3.54920	3.54949	3.55038	3.55059

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.20: GARCH-sged estimation result for Soybean

	garch11sged	garch12sged	garch21sged	garch22sged
omega	.03402**	.04422**	.03412*	.04422**
	(.01294)	(.01532)	(.01395)	(.01647)
alpha1	.07324***	.09336***	.07336***	.09336***
	(.01235)	(.01382)	(.02127)	(.02664)
beta1	.91518***	.58746***	.91504***	.58744***
	(.01426)	(.06113)	(.01804)	(.06903)
skew	.95476***	.95634***	.95478***	.95634***
	(.02043)	(.02070)	(.02068)	(.02082)
shape	1.32803***	1.33134***	1.32793***	1.33134***
	(.05554)	(.05517)	(.05365)	(.05430)
beta2		.30372***		.30375***
		(.05968)		(.05586)
alpha2			.00000	.00000
			(.02689)	(.03470)
AIC	3.54598	3.54581	3.54658	3.54633
BIC	3.55415	3.55562	3.55639	3.55778
SIC	3.54597	3.54580	3.54658	3.54633
HQIC	3.54888	3.54930	3.55007	3.55040

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.21: Component GARCH-normal estimation result for Soybean

	csGARCH11nor	csGARCH12nor	csGARCH21nor	csGARCH22nor
omega	.02830***	.02835***	.02777***	.02777***
	(.00284)	(.00696)	(.00451)	(.00419)
alpha1	.09133**	.09112	.08692*	.08692
	(.02979)	(.07615)	(.03413)	(.08205)
beta1	.26243	.26416	.06901	.06900
	(.18018)	(.18657)	(10.55216)	(3.45495)
eta11	.99109***	.99102***	.99117***	.99117***
	(.00081)	(.00003)	(.00026)	(.00013)
eta21	.07008***	.07001***	.06900***	.06900***
	(.00941)	(.01537)	(.00800)	(.00687)
beta2		.00000		.00000
		(.88148)		(1.41334)
alpha2			.04192	.04192
			(1.43246)	(.45455)
AIC	3.59838	3.59918	3.59851	3.59903
BIC	3.60656	3.60899	3.60832	3.61048
SIC	3.59838	3.59917	3.59850	3.59902
HQIC	3.60129	3.60267	3.60199	3.60310

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.22: Component GARCH-student estimation result for Soybean

	csGARCH11student	csGARCH12student	csGARCH21student	csGARCH22student
omega	.03206***	.03213***	.03152***	.03152***
	(.00498)	(.00709)	(.00543)	(.00543)
alpha1	.04742	.04732	.04614	.04615
	(.02543)	(.06997)	(.02596)	(.08411)
beta1	.16151	.15624	.05864	.05863
	(.22672)	(.58432)	(1.10760)	(2.30326)
eta11	.98676***	.98672***	.98694***	.98693***
	(.00192)	(.00213)	(.00129)	(.00131)
eta21	.05931***	.05934***	.05863***	.05863***
	(.01333)	(.01572)	(.01029)	(.01054)
shape	6.00975***	6.00755***	6.02485***	6.02595***
	(.57452)	(.78518)	(.59411)	(.59135)
beta2		.00000		.00000
		(2.25894)		(1.98241)
alpha2			.01852	.01853
			(.07072)	(.20314)
AIC	3.53355	3.53433	3.53420	3.53472
BIC	3.54336	3.54578	3.54564	3.54780
SIC	3.53355	3.53432	3.53419	3.53471
HQIC	3.53704	3.53840	3.53826	3.53937

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.23: Component GARCH-ged estimation result for Soybean

	csGARCH11ged	csGARCH12ged	csGARCH21ged	csGARCH22ged
omega	.03061***	.03067***	.03002***	.03002***
	(.00406)	(.00495)	(.00444)	(.00530)
alpha1	.06647*	.06636	.06412*	.06412
	(.02633)	(.09122)	(.02740)	(.08325)
beta1	.21618	.21564	.06170	.06169
	(.19383)	(.25018)	(1.65335)	(2.18160)
eta11	.98779***	.98775***	.98797***	.98797***
	(.00001)	(.00075)	(.00035)	(.00049)
eta21	.06253***	.06253***	.06169***	.06169***
	(.00017)	(.01149)	(.00279)	(.01374)
shape	1.34531***	1.34507***	1.34656***	1.34656***
	(.05343)	(.05213)	(.05542)	(.05467)
beta2		.00000		.00001
		(1.32065)		(1.72519)
alpha2			.02813	.02813
			(.15260)	(.22225)
AIC	3.54550	3.54626	3.54600	3.54652
BIC	3.55531	3.55770	3.55744	3.55960
SIC	3.54549	3.54625	3.54599	3.54651
HQIC	3.54899	3.55032	3.55006	3.55117

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.24: Component GARCH-sged estimation result for Soybean

	csGARCH11sged	csGARCH12sged	csGARCH21sged	csGARCH22sged
omega	.03163***	.03168	.03099***	.03099***
	(.00337)	(.03484)	(.00522)	(.00941)
alpha1	.06185*	.06174	.05951	.05950
	(.02538)	(.66144)	(.03975)	(.20959)
beta1	.22135	.22062	.06160	.06159
	(.17521)	(3.79693)	(1.86862)	(9.61218)
eta11	.98741***	.98737***	.98761***	.98761***
	(.00018)	(.03176)	(.00399)	(.03014)
eta21	.06245***	.06245	.06159	.06159
	(.00796)	(.14598)	(.03508)	(.23753)
skew	.95979***	.95985	.95996***	.95996
	(.02114)	(.08776)	(.02142)	(.06259)
shape	1.34147***	1.34123***	1.34281***	1.34280***
	(.05294)	(.17271)	(.05506)	(.06067)
beta2		.00000		.00000
		(18.74527)		(10.35679)
alpha2			.02799	.02799
			(.16267)	(1.12511)
AIC	3.54494	3.54569	3.54543	3.54596
BIC	3.55639	3.55878	3.55852	3.56068
SIC	3.54493	3.54569	3.54542	3.54595
HQIC	3.54900	3.55034	3.55008	3.55119

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.25: GARCH-normal estimation result for Wheat

	garch11normal	garch12normal	garch21normal	garch22normal
omega	.12201	.14283*	.12191	.15975
	(.10409)	(.07020)	(.25133)	(.16590)
alpha1	.06405*	.07597***	.06409**	.07306
	(.02517)	(.01495)	(.02021)	(.05553)
beta1	.90381***	.02394	.90383***	.00000
	(.04813)	(.09569)	(.16638)	(.65178)
beta2		.86146***		.86907
		(.09652)		(.53128)
alpha2			.00000	.01504
			(.10282)	(.14235)
AIC	4.03652	4.03358	4.03702	4.03338
BIC	4.04142	4.04012	4.04356	4.04156
SIC	4.03651	4.03358	4.03701	4.03338
HQIC	4.03826	4.03591	4.03934	4.03629

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.26: GARCH-student estimation result for Wheat

	garch11student	garch12student	garch21student	garch22student
omega	.05550*	.07838**	.05545	.07839**
	(.02460)	(.02588)	(.03549)	(.02821)
alpha1	.04412**	.06226***	.04415*	.06227**
	(.01380)	(.01385)	(.01934)	(.02007)
beta1	.93932***	.39376***	.93932***	.39342***
	(.01958)	(.00965)	(.03240)	(.01270)
shape	8.22333***	8.32984***	8.21973***	8.33049***
	(1.53238)	(1.51732)	(1.43225)	(1.48461)
beta2		.52032***		.52065***
		(.00966)		(.01121)
alpha2			.00000	.00000
			(.03369)	(.02534)
AIC	3.96044	3.96029	3.96095	3.96082
BIC	3.96698	3.96847	3.96912	3.97063
SIC	3.96044	3.96029	3.96094	3.96081
HQIC	3.96276	3.96320	3.96385	3.96430

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.27: GARCH-ged estimation result for Wheat

	garch11ged	garch12ged	garch21ged	garch22ged
omega	.07323	.10458**	.07316	.12056**
	(.04814)	(.03523)	(.76345)	(.04101)
alpha1	.05025*	.07015***	.05028*	.06260***
	(.01999)	(.01313)	(.02082)	(.01310)
beta1	.92948***	.07245	.92949	.00000
	(.03120)	(.07941)	(.62311)	(.06281)
shape	1.42211***	1.42737***	1.42209***	1.42891***
	(.12471)	(.12283)	(.12955)	(.12347)
beta2		.82770***		.88339***
		(.08233)		(.05350)
alpha2			.00000	.02010
			(.44058)	(.01946)
AIC	3.98459	3.98359	3.98510	3.98361
BIC	3.99113	3.99176	3.99327	3.99342
SIC	3.98459	3.98358	3.98509	3.98360
HQIC	3.98691	3.98649	3.98800	3.98710

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.28: GARCH-sged estimation result for Wheat

	garch11sged	garch12sged	garch21sged	garch22sged
omega	.06742	.09798**	.06735	.11027**
	(.03712)	(.03340)	(.08628)	(.03583)
alpha1	.05035**	.07240***	.05037**	.06422***
	(.01618)	(.01308)	(.01591)	(.01661)
beta1	.93088***	.12244	.93090***	.01263
	(.02428)	(.08175)	(.07549)	(.10181)
skew	1.11292***	1.12075***	1.11294***	1.11651***
	(.03226)	(.03080)	(.03277)	(.03276)
shape	1.45767***	1.46787***	1.45764***	1.46702***
	(.12170)	(.12040)	(.11808)	(.11940)
beta2		.77718***		.87406***
		(.08066)		(.09015)
alpha2			.00000	.01783
			(.05749)	(.02488)
AIC	3.97939	3.97782	3.97989	3.97823
BIC	3.98756	3.98763	3.98970	3.98967
SIC	3.97938	3.97781	3.97989	3.97822
HQIC	3.98229	3.98130	3.98338	3.98229

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.29: Component GARCH-normal estimation result for Wheat

	csGARCH11nor	csGARCH12nor	csGARCH21nor	csGARCH22nor
omega	$.06849^{***}$	$.06804^{***}$	$.06851^{***}$	$.06722^{***}$
	(.01340)	(.00849)	(.01137)	(.00872)
alpha1	$.05027^{*}$	.05983	.04955	.06091
	(.02112)	(.03435)	(.02961)	(.03578)
beta1	$.72302^{***}$	.00000	$.72025^{***}$	.00000
	(.07783)	(.09998)	(.06097)	(.22558)
eta11	$.98100^{***}$	$.98105^{***}$	$.98100^{***}$	$.98126^{***}$
	(.00034)	(.00025)	(.00000)	(.00023)
eta21	$.03264^{***}$	$.03256^{**}$	$.03266^{**}$	$.03189^{*}$
	(.00164)	(.01124)	(.01131)	(.01262)
beta2		$.64477^{***}$		$.63162^{***}$
		(.13071)		(.12382)
alpha2			.00174	.00443
			(.00188)	(.02899)
AIC	4.03418	4.03375	4.03483	4.03426
BIC	4.04236	4.04356	4.04465	4.04570
SIC	4.03418	4.03375	4.03483	4.03425
HQIC	4.03709	4.03724	4.03832	4.03833

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.30: Component GARCH-student estimation result for Wheat

	csGARCH11student	csGARCH12student	csGARCH21student	csGARCH22student
omega	.04422***	.04259***	.04421***	.04258***
	(.00481)	(.00467)	(.00459)	(.00464)
alpha1	.02718	.03409*	.02716	.03412*
	(.01523)	(.01568)	(.02467)	(.01578)
beta1	.66315	.00000	.66144	.00000
	(.39448)	(.16489)	(.36088)	(.17867)
eta11	.98597***	.98650***	.98597***	.98651***
	(.00025)	(.00018)	(.00020)	(.00016)
eta21	.03425***	.03272***	.03425***	.03271***
	(.00296)	(.00188)	(.00248)	(.00210)
shape	8.53886***	8.55534***	8.53664***	8.55366***
	(1.57940)	(1.54463)	(1.53096)	(1.55135)
beta2		.68613***		.68588***
		(.17801)		(.14343)
alpha2			.00000	.00006
			(.02347)	(.01630)
AIC	3.96031	3.96060	3.96095	3.96112
BIC	3.97013	3.97205	3.97240	3.97420
SIC	3.96031	3.96059	3.96095	3.96111
HQIC	3.96380	3.96467	3.96502	3.96577

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.31: Component GARCH-ged estimation result for Wheat

	csGARCH11ged	csGARCH12ged	csGARCH21ged	csGARCH22ged
omega	.05090***	.05005***	.05089***	.04971***
	(.00724)	(.00670)	(.00717)	(.00699)
alpha1	.03843*	.04553***	.03840	.04607*
	(.01640)	(.00232)	(.02218)	(.01912)
beta1	.70025***	.00000	.70043***	.00000
	(.11430)	(.14303)	(.12594)	(.13862)
eta11	.98503***	.98526***	.98503***	.98535***
	(.00021)	(.00003)	(.00007)	(.00011)
eta21	.03268***	.03196***	.03267***	.03166***
	(.00300)	(.00744)	(.00188)	(.00140)
shape	1.43115***	1.43263***	1.43102***	1.43274***
	(.12692)	(.12612)	(.12664)	(.12536)
beta2		.66504***		.65688***
		(.14172)		(.10967)
alpha2			.00000	.00209
			(.02359)	(.01943)
AIC	3.98383	3.98393	3.98446	3.98445
BIC	3.99364	3.99538	3.99590	3.99753
SIC	3.98382	3.98392	3.98445	3.98444
HQIC	3.98731	3.98800	3.98852	3.98910

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Table A.32: Component GARCH-sged estimation result for Wheat

	csGARCH11sged	csGARCH12sged	csGARCH21sged	csGARCH22sged
omega	.04757***	.04634***	.04760***	.04635***
	(.00544)	(.00641)	(.00646)	(.00637)
alpha1	.04116*	.05041*	.04119	.05041*
	(.02094)	(.02141)	(.02504)	(.02099)
beta1	.61625*	.00000	.61197*	.00000
	(.27943)	(.24607)	(.30001)	(.19095)
eta11	.98579***	.98611***	.98578***	.98610***
	(.00001)	(.00020)	(.00018)	(.00017)
eta21	.03341***	.03237***	.03344***	.03236***
	(.00826)	(.00274)	(.00283)	(.00249)
skew	1.11776***	1.12029***	1.11777***	1.12028***
	(.03206)	(.03118)	(.03215)	(.03121)
shape	1.47042***	1.47419***	1.47031***	1.47420***
	(.12199)	(.12045)	(.12176)	(.12039)
beta2		.55344		.55357***
		(.31806)		(.15005)
alpha2			.00000	.00000
			(.02090)	(.02187)
AIC	3.97822	3.97813	3.97885	3.97865
BIC	3.98967	3.99121	3.99193	3.99337
SIC	3.97821	3.97812	3.97884	3.97864
HQIC	3.98229	3.98278	3.98350	3.98388

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$ The null hypothesized value for shape estimate is 1

Table A.33: Diebold Mariano Test Result for Comparing Standard GARCH and Component GARCH with Corn Returns

	DM Statistic	Different	More	Less
nor11	2.19111	0.02850	0.01425	0.98575
nor12	2.21748	0.02665	0.01332	0.98668
nor21	1.41010	0.15859	0.07930	0.92070
nor22	1.30946	0.19046	0.09523	0.90477
std11	11.07024	0.00000	0.00000	1.00000
std12	11.15305	0.00000	0.00000	1.00000
std21	10.31488	0.00000	0.00000	1.00000
std22	12.99777	0.00000	0.00000	1.00000
ged11	5.00560	0.00000	0.00000	1.00000
ged12	5.20175	0.00000	0.00000	1.00000
ged21	4.06841	0.00005	0.00002	0.99998
ged22	4.70444	0.00000	0.00000	1.00000
sged11	4.57598	0.00000	0.00000	1.00000
sged12	4.78372	0.00000	0.00000	1.00000
sged21	3.55888	0.00038	0.00019	0.99981
sged22	4.24820	0.00002	0.00001	0.99999

Table A.34: Diebold Mariano Test Result for Comparing Standard GARCH and Component GARCH with Rice Returns

	DM Statistic	Different	More	Less
nor11	7.24446	0.00000	0.00000	1.00000
nor12	9.08411	0.00000	0.00000	1.00000
nor21	7.14773	0.00000	0.00000	1.00000
nor22	9.07991	0.00000	0.00000	1.00000
std11	-2.03309	0.04211	0.97894	0.02106
std12	-1.70304	0.08864	0.95568	0.04432
std21	-1.81598	0.06945	0.96527	0.03473
std22	-1.70141	0.08895	0.95553	0.04447
ged11	0.40128	0.68824	0.34412	0.65588
ged12	0.87311	0.38266	0.19133	0.80867
ged21	0.62174	0.53415	0.26707	0.73293
ged22	0.71149	0.47682	0.23841	0.76159
sged11	-0.26872	0.78816	0.60592	0.39408
sged12	0.87287	0.38279	0.19140	0.80860
sged21	0.09840	0.92162	0.46081	0.53919
sged22	0.86812	0.38538	0.19269	0.80731

Table A.35: Diebold Mariano Test Result for Comparing Standard GARCH and Component GARCH with Soybean Returns

	DM Statistic	Different	More	Less
nor11	3.59347	0.00033	0.00017	0.99983
nor12	3.53168	0.00042	0.00021	0.99979
nor21	3.27259	0.00108	0.00054	0.99946
nor22	2.97149	0.00298	0.00149	0.99851
std11	5.55997	0.00000	0.00000	1.00000
std12	6.53633	0.00000	0.00000	1.00000
std21	5.02785	0.00000	0.00000	1.00000
std22	5.33341	0.00000	0.00000	1.00000
ged11	3.84911	0.00012	0.00006	0.99994
ged12	3.94633	0.00008	0.00004	0.99996
ged21	3.46625	0.00053	0.00027	0.99973
ged22	3.24475	0.00119	0.00059	0.99941
sged11	3.96010	0.00008	0.00004	0.99996
sged12	4.10381	0.00004	0.00002	0.99998
sged21	3.52917	0.00042	0.00021	0.99979
sged22	3.30586	0.00096	0.00048	0.99952

Table A.36: Diebold Mariano Test Result for Comparing Standard GARCH and Component GARCH with Wheat Returns

	DM Statistic	Different	More	Less
nor11	3.69881	0.00022	0.00011	0.99989
nor12	1.31733	0.18781	0.09390	0.90610
nor21	3.61007	0.00031	0.00016	0.99984
nor22	2.34315	0.01917	0.00959	0.99041
std11	4.29298	0.00002	0.00001	0.99999
std12	4.45609	0.00001	0.00000	1.00000
std21	4.26438	0.00002	0.00001	0.99999
std22	4.41715	0.00001	0.00001	0.99999
ged11	3.73669	0.00019	0.00009	0.99991
ged12	1.71874	0.08574	0.04287	0.95713
ged21	3.71154	0.00021	0.00010	0.99990
ged22	3.10018	0.00195	0.00097	0.99903
sged11	3.89209	0.00010	0.00005	0.99995
sged12	2.95770	0.00312	0.00156	0.99844
sged21	3.86770	0.00011	0.00006	0.99994
sged22	3.39736	0.00069	0.00034	0.99966