Energy and Agricultural Commodity Markets Interaction: An Analysis of Crude Oil, Natural Gas, Corn, Soybean, and Ethanol Prices

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ABSTRACT

This paper broadens the analysis of the interactions between energy and agricultural commodity markets by focusing on five major commodities: oil, natural gas, soybean, corn, and ethanol, and intends to provide more updated information regarding the degree of the connection among the markets. We estimate a DCC-MGARCH model to accommodate the dynamic and changing degree of interconnections among the five markets with respect to price levels and price volatilities. In doing so, we control for additional economic variables including oil and gas inventories, interest rate spread, exchange rate and economic activities. Our empirical evidence suggests that there are varying degrees of interconnections among the energy and agricultural commodities in the long term as well as the short term, but the interactions among the agricultural commodities and ethanol are generally higher than the interactions between oil and gas and agricultural markets. In addition, we reveal some weak evidence of commodity market speculation. The estimated conditional volatility correlations suggest that volatility spillovers among the markets were time dependent and dynamic.

Keywords: Volatility spillover, Commodity markets connections, Oil and gas prices, Ethanol, Corn, and Soy bean prices, Ethanol policy, DCC-MGARCH

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1. INTRODUCTION

This paper empirically studies the connections between agricultural and energy commodity markets with a focus on five commodities—crude oil, natural gas, corn, soybean, and ethanol, hoping to shed light on how these markets are related in terms of price level and volatility in a more recent period. The study intends to provide more updated empirical evidence on whether or to what degree these commodity markets are connected, and whether these connections, if there are any, make any sense based on economic explanation of the linkages among the markets.

We believe the study is timely as there is a growing literature on the interaction of energy and agricultural commodity markets. These new and renewed interests have been triggered by at least two recent events in the commodity markets. One such event is the phenomenal increase in the volume of trading in these markets during the period from 2000 to 2008. Cevik and Sedik (2011)

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suggested that such events as the global financial crisis and the commodity price volatility during the period have heightened interest in the dynamic relationships among the commodity markets. A common theme of the explanation of this growth in virtually all commodity markets during the period is financialization of the commodity markets (Henderson et al., 2015; etc.). Frankel (2014) presented some evidence that supported the argument that both speculation and easy monetary policy had contributed to commodity price changes and their volatilities. Gozgor et al (2016) found some evidence of financialization in the corn and soybean markets. Sockin and Xiong (2015) suggested that noises in futures trading of the commodities would feed back into the demand of commodity producers and the producers had difficulties to tell whether the change was due to financial trading or global demand change due to information frictions. Cheng and Xiong (2014) found evidence to support the claim that financialization had fundamentally changed the functions of the risk sharing and price discovery of the commodity markets. While these studies confirmed to a degree that financialization in general and speculation in particular had affected the commodity markets as a whole, not all studies agreed that financialization or speculation had a leading effect on sharp increases in commodity prices (for example, the case of oil in Knittel and Pindyck (2016)). Even though Knittel and Pindyck (2016) did not directly address the issue of connections between oil and commodity markets, their results implied that speculation could not be the main factor that drove the co-movement of the commodity prices.

The other factor behind the renewed interest in the connections between energy and agricultural commodity markets is the worldwide ethanol policy, especially in the U.S., which called for cleaner and lower-cost ethanol to replace traditional hydrocarbons such as oil. The Renewable Fuels Standard (RFS2) as established by the 2007 Energy Independence and Security Act requires an increasingly larger number of renewable sources of fuel including biofuels into the fuel mix. Other countries especially Brazil and European Union also ramped up the production of biofuels to supplement gasoline in especially transportation. Serra and Zilberman (2013) had a nice review of the literature on the bio-fuel related price transmission for the energy and agricultural markets with focuses on mainly three commodities—crude oil, ethanol, and corn. Serra and Zilberman (2013) pointed out that even though the results are mixed, most of price transmissions went from oil market to ethanol market and then to corn market. In addition, many studies focused on price transmissions and there was a need for more studies on volatility transmissions. Furthermore, most of the studies only examined the transmission mechanism in the context of time series models without incorporating economic variables. To address this last point, we include several relevant economic variables to control for any possible effects of these variables on returns and volatilities of the commodity prices to better understand how shock from one market affects the others. By directly controlling for these variables, we can directly measure how these economic variables have impacted the commodity prices and better capture the shocks in the commodity prices to study the interactions. In addition, we expand the number of energy and agricultural commodity variables.

The energy and agricultural markets can be interrelated due to the same set of economic forces that influence them and to unavoidable cross-market arbitrage activities (de Gorter et al., 2008). Agricultural production processes use energy products such as oil and natural gas; thus, energy prices directly and indirectly affect the input and transportation cost of the agricultural products. The increase in oil and gas prices generates an incentive to use biofuels and other alternative energy sources; thus, an increase in the price of biofuels such as ethanol would also increase the prices of some agricultural products, namely food prices, directly. In addition, economic policies concerning biofuels can directly or indirectly strengthen or weaken these relationships. This discussion suggests that relationships among the markets are time-varying and dynamic.

Economic forces have also been cited in the literature to have caused the commodity markets to move together. These factors include economic activities, speculation (inventories have been used to bear on the role of speculations despite of some unsettlements on this issue), and monetary policy (Frankel (2014)). In addition to some of these macroeconomic variables, Gilbert (2010) also suggested that dollar exchange rate would be a factor that could influence commodity prices as originally analyzed by Ridler and Yandle (1972). Gozgor and Kablamaci (2014) also suggested that speculation and financialization could be the driving factors behind the co-movement of the commodity prices. Even though this paper does not directly address the role of speculation in the movement of the commodity prices, by incorporating these exogenous economic variables directly, our study helps to understand the possible co-movement of the commodity prices and to what degree these factors could directly influence the commodities.

To thoroughly understand the price level and volatility connections among these markets is important in several aspects. Most motivations for these studies have focused on the importance of food markets in an economy. This is an especially important issue for developing countries, as food makes up a greater share in their spending than in more developed countries, so problems in the food sector can threaten the food security of those countries and undermine their food price stabilization policies. Due to the substitutability of foodstuffs, if there is a close relationship between the price level and volatility of the agricultural and energy commodities, then the higher price and volatility in the corn and soybean markets due to energy market price volatility could spill over to other agricultural sectors such as wheat and so on. In addition, the co-movement of energy and commodity prices can make financial diversification programs less effective. This could be an increasingly important issue, as increasingly agricultural commodities have been included in financial investment portfolios. Furthermore, the increase in price volatility of agricultural commodities could increase the cost of risk management programs and thus the cost of foodstuffs in general. Consequently, it is extremely important to understand the extent of energy and agricultural product price interactions and, in particular, the transmission of price volatility between the markets.

We study five energy and agricultural commodities: oil, natural gas, ethanol, corn, and soybean and these commodities are selected based on the linkages amount them. It is generally accepted that oil and gas are highly connected as they are both substitutable to a certain degree in technology. Both oil and gas are also associated in the extraction and production process. However, despite of the association in production, substitutability in consumption may be limited to a certain degree. In addition, oil and gas are driven by different sets of variables. Therefore, the price and volatility connection between oil and gas may be time dependent. Among the five variables we consider, ethanol is the variable that connects the energy and commodity markets explicitly as ethanol is used as an alternative to traditional energy. We include corn and soybean in the system as ethanol can be extracted from corn as well as soybeans even though the extraction of ethanol from soybean is to a much lesser degree. The agricultural commodity markets can also be connected to the energy market through other links as oil and natural gas can be the energy used in the agricultural commodity production process.

We study these interactions for separate markets—spot and futures. Even though we will not be able to directly measure the feedback effect of the futures market on the spot market, the existence/lack of possible difference in the interaction patterns in the spot and futures markets may provide additional information about the energy and agricultural commodity market connections. As spot market is more influenced by physical supply of and demand for the commodity, the differentiation of the impacts from both the spot and futures markets may be an indication that the financial (futures) markets may be impacted differently by the financialization than the spot market.

This paper utilizes the multivariate GARCH (MGARCH) approach to study the dynamics and cross-dynamics of price and price volatility in oil, natural gas, ethanol, corn, and soybean markets for the period from 2005 to 2017. The price interactions are captured by the mean equation of the variables, and the volatility connections are measured by the conditional variance correlations. In modeling the volatility interaction, we estimate the time-varying or dynamic conditional correlation (DCC). The estimated conditional correlations from the DCC-MGARCH model are then examined further to study the patterns in the volatility interactions among the five commodities. In this process, we investigate specifically how energy price and price volatility stimulate price and price volatility in the corn and soybean markets. We also model directly how the ethanol price is intertwined in between the energy and agricultural commodities. Our approach would enable us to find whether the degree of interconnection across markets changes over time. Furthermore, to understand better the interactions between the markets, we control for the effects of several variables that have been cited to influence these commodities.

Our intended contributions are several folds. First, past studies mostly focused on a smaller set of commodities (mostly oil and gas or oil, ethanol, and corn). We include a more comprehensive list of relevant commodities. Our study covers oil, natural gas, and ethanol along with corn and soybean. Our study also directly measures the possible influence of some exogenous variables such as exchange rate, interest rate, inventory, and economic activity. Directly controlling for the effects of these variables would enable us to see how the commodity prices can be influenced by these economic variables. In addition, it would enable us to better understand the interaction of the commodities after we account for the influence of these exogenous variables. Thirdly, we also model our systems using spot and futures prices. Even though we will not be able to detect the "feedback effect" of the futures market on the spot market directly (Sockin and Xiong (2015), our study would enable us to compare the results obtained from the futures market and spot market and detect any significant differences. Fourth, our study provides a direct measure of time-varying volatility connections among the commodity price variables. These connections would reflect better the connections among the commodities since we control for the impact of some common economic variables.

The remainder of the paper is organized as follows. The next section provides a brief overview of related literature about price interconnections and volatility spillovers between energy and commodity markets. Section 3 presents the empirical approach used to examine price connection and volatility transmission between these markets. Section 4 describes the data and their sources. Section 5 shows and discusses the estimation results. Section 6 concludes and provides some policy implications.

2. RELATED LITERATURE

2.1 Price Connection and Volatility Spillover between Energy and Agricultural Commodity Markets

Many studies investigated the connection between energy commodity prices and agricultural commodity prices, even though the commodity set varied from study to study. Trujillo-Barrera, Mallory, and Garcia (2012) used futures prices to analyze recent price volatility spillovers from crude oil to other markets in the United States. Their findings suggested similar timing and magnitudes of crude oil spillovers to the corn and ethanol markets, with a slightly stronger effect on the ethanol market. The crude oil market contributed to about 10–20% of the corn and ethanol market price volatility, with about 45% of the contribution coming during the period of financial crisis when the demand for oil changed significantly. There was some evidence of intermarket transmission between the corn and ethanol markets, with the corn market affecting the ethanol market but not vice versa.

Employing a multivariate GARCH model, Gardebroek and Hernandez (2013) studied the interactions among the same markets—crude oil, corn, and ethanol. Their empirical results suggested similar but slightly different findings: (1) there was a significant volatility spillover from corn to the ethanol market but not the opposite; (2) the interaction of corn and ethanol markets increased in more recent years, especially after 2006, when ethanol became the sole alternative oxygenate for gasoline; and (3) there was no major volatility spillover from crude oil to the corn market. Their empirical results did not support the concept that volatility in energy markets stimulated price volatility in the corn market.

Also using a multivariate GARCH framework but expanding the list of the energy and agricultural products to include corn, soybean, gasoline, and oil, Zhang et al. (2009) found no significant long-term relationships between the agricultural and energy price levels. They also failed to find any significant volatility spillovers among these markets. One of the innovations in their study is that they divided the sample into two subperiods: the ethanol preboom era of 1989 to 1999 and the ethanol boom period of 2000 to 2007.

Employing stochastic volatility models to study the interconnections between crude oil, corn, and wheat markets, Du et al. (2011) found no significant interconnections between the markets for the first sample from 1998 to 2006, a result that is consistent with Zhang et al. (2009). But their result is different for the second half of their sample period, from October 2006 to January 2009, during which the crude oil market significantly influenced the corn market in terms of volatility. This result can be explained by the fact that the increased ethanol production heightened the connection between the crude oil market and the corn market. This result was supported by further evidence in Wu et al. (2011), who found that after the introduction of the 2005 Energy Policy Act, the oil and corn markets were much more interconnected. Furthermore, they found that after a certain threshold level of ethanol and gasoline consumption, the corn price was heavily influenced by movement in the crude oil price. Harri and Darren (2009) also provided further evidence of crude oil price influencing the corn price level and volatility.

Using equilibrium models and simulations, others (e.g., Thompson, Meyer, and Westhoff, 2009; Yano, Blandford, and Surry, 2010; Hertel and Beckman, 2011) looked into the connection between the crude oil and agricultural markets and examined the possible impact of biofuel policies such as tax credits and mandates on that connection. Their results generally supported the proposition that such policies strengthen the connection between the energy and agricultural markets.

Several studies have examined price volatility transmission between energy and agricultural markets. For example, Zhang et al. (2009) studied the volatility transmission between food markets and energy markets in the United States for the period from 1989 to 2007. Serra et al. (2011) studied the connection between the ethanol, sugarcane, and crude oil markets in Brazil from 2000 to 2008. Wu et al. (2011) studied the U.S. corn and oil markets for the period from 1992 to 2009. Du et al. (2011) studied the interconnections between crude oil, corn, and wheat from 1998 to early 2009 to understand the volatility spillover from the oil market to the corn and wheat markets. In addition, Trujillo-Barrera et al. (2012) investigated the relationship between futures prices of crude oil, ethanol, and corn for the period from 2006 to 2011. Nazlioglu et al. (2013) investigated volatility transmission among the price of oil and the prices of wheat, corn, soybean, and sugar. In these endeavors, various empirical methods have been employed: the BEKK model of Engle and Kroner (1995) by Zhang et al. (2009) and Serra et al. (2011), semiparametric MGARCH models (Serra (2011), a restricted asymmetric MGARCH model (Wu et al. 2011 and Trujillo-Barrera et al. 2012), and testing for causality in variance based on estimating univariate GARCH models (Nazlioglu et al. (2013)).

Cabrer and Schulz (2016) investigated the price and volatility risk between crude oil and biodiesel, as well as the price and volatility of rapeseed, in Germany, examining the dynamic relationship between them over time. They did not find evidence that biodiesel causes high and volatile agricultural commodity prices. Moreover, Gozgor and Memis (2015), for the period of 2006 to 2013, examined the price volatility spillovers among crude oil, soybeans, corn, wheat, and sugar futures markets using the Yang-Zhang estimators for historical volatility. They found that there was volatility spillover from the crude oil market to the corn market, and from both the soybean and corn markets to the wheat market.

Various explanations have been offered for the increase in the agricultural product prices and their volatilities (Baffes, 2011; Gilbert and Morgan, 2010; Irwin and Good, 2009). Among these factors, rapid economic growth in developing countries (especially in China and India), low inventory levels, loose monetary and expansionary fiscal policies, depreciation in the U.S. dollar, and diversion of food crops into biofuel production all have contributed to higher and more volatile agricultural product prices. Moreover, policy-induced connection has received particular attention, as ethanol production to replace traditional energy as a global movement dictated by various countries' policies has changed the relationship between the energy and agricultural markets (Hertel and Beckman, 2011; Muhammad and Kebede, 2009; Tyner, 2008). In light of this relationship, one would expect higher price volatility in the energy markets to be transmitted into the agricultural markets. As corn and soybeans (to a lesser degree) are the main crops used in the production of biofuels, we would expect volatility spillover between the energy price, especially the oil price, and the corn and soybean prices.

While there appear to be studies of connections between the oil market and corn and ethanol markets, studies on the connections between natural gas price and others such as corn, soybean and ethanol prices are rare. However, natural gas and the agriculture sector in general, and corn, soybean, and ethanol markets in particular, can be related even though the degree of the connection is largely unknown. Natural gas is a feedstock in the production of fertilizers and pesticides. In addition, natural gas has been used in dry milling, the most common process for making ethanol. Natural gas is also used in the powering of farm house machinery. These connections suggest that higher natural gas prices are expected to push up the costs of producing corn, soybean, leading to higher corn, soybean and ethanol prices. In the meantime, demand for biofuels, and thus demand for more corn and soybeans, could also push up the price of natural gas.

The two studies that have studied such relationships include Whistance et al. (2010) and Whistance and Thompson (2009). In terms of price linkages, Whistance el al. (2010) found very little impact of U.S. biofuel tax credits and other policies on natural gas use and thus very little, if any, change in natural gas prices. However, their study made a few special assumptions. First, they assumed a one-way linkage from crop and biofuel markets to the natural gas market, while linkage in the other direction is possible. Second, the petroleum price was assumed to be exogenous, which is a strong assumption, as there could be substitutions between petroleum products and natural gas; and oil prices could be influenced by the prices of corn and ethanol, at least in theory. In a similar and more detailed study, Whistance and Thompson (2009) studied the impact of the biofuel policy and production on natural gas consumption and thus prices, finding small but significant effects. The explanation of these small effects stems from the fact that the demand for gas from the corn and ethanol sectors is small compared to the overall demand for natural gas. Nowhere, however, were the linkages in the volatilities of these markets considered.

2.2 Time-Varying Relationships between the Markets

One of the key findings of the connection between the energy and agricultural markets is that the relationship varies over time. The reasons for such a non-constant relationship come from both demand and supply sides. According to Meyer and Thompson (2010), the ethanol demand curve is highly nonlinear due to varying price elasticities, as the sources of the demand for ethanol vary. Demand for ethanol when ethanol is used as an oxygenate to gasoline is price inelastic; when ethanol is a competitive substitute for gasoline, demand for ethanol is elastic; and when ethanol is used as blending in flex-fuel cars and the maximum amount of ethanol can be absorbed, the demand for ethanol is again inelastic. On the other hand, the ethanol supply can have different phases of price elasticity as well: high price elasticity when the ethanol production capacity is low and high price inelasticity when the ethanol production capacity is high. As the degree of elasticity varies with supply and demand conditions, the effect of oil and gas on corn and ethanol will also vary over time. Furthermore, biofuel policies such as mandates and tax credits are expected to complicate the relationship as well, as these policies could increase the demand for ethanol. For an overview of biofuel policies, see Sorda et al. (2010).

To account for the time-varying relationship between the prices of oil, natural gas, corn, soybean and ethanol, we properly implement an econometric method of price level and price volatility to study the interactions and dynamics among the markets across time.

3. DATA

The data used for our analysis are weekly prices for U.S. crude oil, natural gas, ethanol, corn, and soybean from March 15, 2005, through October 18, 2017 (657 observations), during which there were significant changes in biofuel use mandates. The spot oil price is the West Texas Intermediate crude oil FOB spot price obtained from the Energy Information Administration (EIA). The spot agricultural commodities are the No. 2 yellow corn FOB Gulf price and No. 1 yellow soybean, reported by the Food and Agriculture Organization (FAO). The spot natural gas price is the Henry Hub spot price obtained from EIA as well. The ethanol price is dollars per gasoline equivalent gallon (rack prices) collected from EIA. We also obtained the futures price of the five commodities from the same respective sources. In our analysis, prices are transformed by applying the natural logarithm.

We have collected the information on control variables from various sources. Both world crude oil stock and U.S. natural gas storage are obtained from EIA. We have collected the data on interest rate spreads (measured by 10-Year Treasure Bill minus Federal Funds Rate) and Trade Weighted U.S. Dollar Index (Broad) form Federal Reserve Bank of St. Louis (fred.stlouisfed.org). Global real economic activity (Killian's Economic Index) is obtained from the estimates by Killian (http://www-personal.umich.edu/~lkilian).

4. METHODOLOGY

Our approach to modeling the volatility spillover follows the studies of Bekaert and Harvey (1997), Ng (2000), Bekaert, Harvey, and Ng (2005), Baele (2005), and Christiansen (2007). These studies all focused on international equity and bond markets. In this study, however, we investigate spillovers across two types of market (energy and agricultural) and five commodities (crude oil, natural gas, corn, soybean, and ethanol). We employ a multivariate GARCH approach to study the level of interdependence and the dynamics of volatility among oil, natural gas, ethanol, corn, and soybean markets in the United States. Specifically, we estimate a dynamic conditional correlation (DCC-MGARCH) model. As it is flexible enough to account for its own and cross-market volatility and persistence across markets, the BEKK model has been used to study the dynamic relationships among price and price volatilities. The DCC model provides a dynamic conditional correlation matrix, which enables us to study whether the cross-market interdependence does or does not vary over time.

We study the price behavior as in the following model,

$$r_t = \alpha + \beta \times ECM_t + \sum_{i=1}^{n} \gamma_i \times r_{t-i} + \sum_{j=1}^{n} \delta_j \times \Omega_{j,t} + \sum_{k=1}^{n} \phi_k \times SB_{k,t} + \lambda \times GFC_t + \varepsilon_t, \qquad (1)$$
$$\varepsilon_t \left| I_{t-1} \right. \sim (0, H_t)$$

where r_t is a 5 × 1 vector of returns for oil, natural gas, soybean, corn, and ethanol; α is defined as a 5 × 1 vector of long-term drifts; γ_i and δ_j, $i\,(j) = 1, \ldots, n$ are 5 × 5 parameter matrices; ECM_t is a cointegration vector estimated from Error Correction Model (ECM), representing the stationary linear combination or long-run equilibrium relationship among the energy and agricultural commodities; Ω is a vector of control variables, namely, world oil inventory, U.S. gas inventory, interest rate spread, exchange rate and world economic activity. For our design, we restricted oil price to be influenced by world oil inventory, gas prices to be influenced by gas inventory, and all five commodity price variables to be influenced by other control variables. In addition, we have included a series of break dummies (SB) to try to capture the possible effects of the breaks in the series. These break dummies (SB) represent the global food crisis (2008–2009) and respective structural breaks we detected in each series as we will explain in the section below. The food crisis dummy (GFC) is inserted in the equations of all commodities while each commodity has its own break dummies based on the test result of breaks. Please note that the period for the food crisis is rather general (2008 to 2009) and it overlaps with the great recession during which commodity prices collapsed. Therefore, the dummy GFC may be a misnomer as there is no way we can disentangle the effect of the food crisis and recession on the commodity return and volatility. ε_t is a 5 × 1 vector of forecast errors for the best linear predictor of r_t. The forecast error is conditional on past information (I_{t-1}), and the error has a corresponding variance–covariance matrix H_t. The elements of β_j, j=1, …, k provide measures of own- and cross-mean spillovers between markets as in a standard VAR representation.

We define the conditional variance-covariance matrix H_t as

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'H_{t-1}G + \sum_{l=1}^{n} \theta_l \times SB_{l,t} + \omega \times GFC_t, \qquad (2)$$

where C is a 5 × 5 upper triangular matrix of constants c_{ij}, A is a 5 × 5 matrix containing elements a_{ij} that measure the degree of innovation from market i to market j, and G is a 5 × 5 matrix whose elements g_{ij} show persistence in conditional volatility between markets i and j. We also included the event dummies such as the world food crisis (GFC) and individual breaks (SB) detected in each price series in the conditional variance-covariance equation. The conditional variance–covariance matrix defined in Eq. (2) allows us to study the volatility transmission across markets in terms of its persistence, direction, and magnitude.

A DCC model assumes a time-dependent conditional correlation matrix R_t=($\rho_{ij,t}$), i, j = 1, …, 5, and the conditional variance–covariance matrix H_t

$$H_t = D_t R_t D_t, \qquad (3)$$

where

$$D_t = diag\left(\sqrt{h_{11,t}},\ldots\ldots,\sqrt{h_{33,t}}\right), \tag{4}$$

$h_{ij,t}$ is assumed to follow a GARCH (1,1) specification, i.e., $h_{ii,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + h_{ii,t}$, i = 1,…, 5, and

$$R_t = diag\left(q_{ii,t}^{-1/2}\right) Q_t diag\left(q_{ii,t}^{-1/2}\right), \tag{5}$$

with the 5 × 5 symmetric positive-definite matrix $Q_t = (q_{ij,t})$, $i, j = 1,2, \ldots, 5$, given by

$$Q_t = (1-\lambda_1-\lambda_2)\overline{Q} + \lambda_1 u_{t-1}u'_{t-1} + \lambda_2 Q_{t-1} \tag{6}$$

and $u_{it} = \varepsilon_{it} / \sqrt{h_{ii,t}} \cdot \overline{Q}$ is the 5 × 5 unconditional variance matrix of u_t, and λ_1 and λ_2 are nonnegative adjustment parameters satisfying $0 < \lambda_1 + \lambda_2 < 1$.

5. EMPIRICAL RESULTS

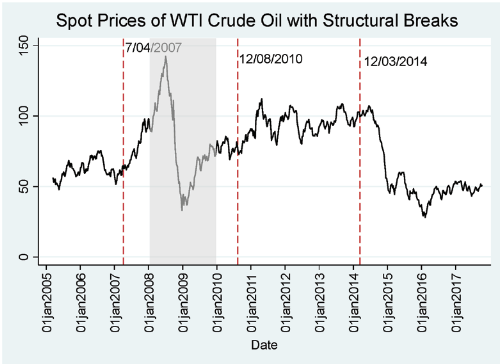
5.1 Descriptive Statistics

Figure 1 plots the spot price of crude oil, natural gas, corn, soybean, and ethanol, with multiple structural breaks identified by Bai and Perron (2003) approach. There are some distinctive patterns in the series. All prices fluctuated wildly during the sample period. First, all prices were moving upward or already at high levels at the beginning of the sample period as our sample started in the middle of the 2000–2008 period. Several prices including crude oil and natural gas followed a downward trend later except the prices of corn and soybean. Most prices experienced collapses again around 2014 except natural gas price as natural gas price stayed low after the 2008 collapse. Second, oil price and the prices of agricultural commodities, corn and soybean, appeared to have shared a very similar pattern: increasing at the beginning of the sample period and then declining during the period of 2008 and 2009, followed by a period of high prices before declining again around the end of 2014. Natural gas price did not follow such as pattern, nor did ethanol price. Third, these prices experienced several structural breaks during the sample period. The dotted lines represent the breaks as detected by the method of Bai and Perron (2003). While crude oil price, corn price and ethanol price experienced three breaks, gas price and soybean price each experienced two breaks. The break information is used in our modeling of the commodity prices in a later section. Finally, Figure 1 also plots the period of world food crisis in a shaded area for the period of 2008 and 2009 during which all commodity prices experienced an up and down pattern. Similarly, Figure 2 shows the futures price of crude oil, natural gas, corn, soybean, and ethanol, segmented with multiple structural breaks as well. We find the time series patterns in futures prices to be similar to those in spot prices.

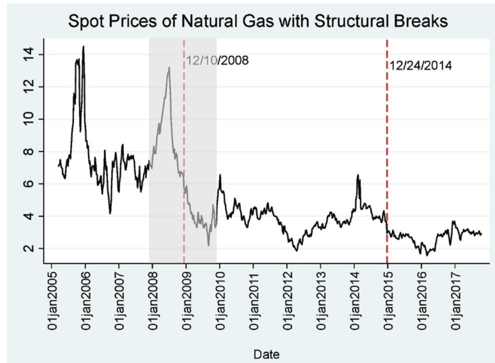
Table 1 summarizes descriptive statistics of spot and futures prices of the five commodities. Both spot and futures prices show similar values of mean, standard deviation, minimum and maximum. Please note that the measuring units of oil, gas and ethanol prices are the same for both spot and futures (dollars per barrel, dollars per MMBtu, and dollars per gallon respectively). However, the measuring units of corn and soybean prices are different with spot prices being measured by dollars per bushel and futures prices being measured by cents per bushel.

All commodity prices show significant volatilities. For example, crude oil price (both spot and futures) had a mean price of about $74 and a standard deviation of $23. While gas price had a

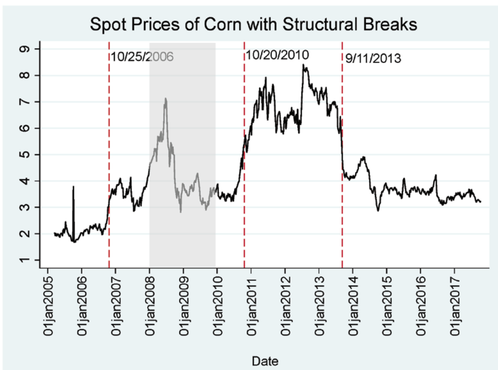
Figure 1: Spot Prices of Energy and Agricultural Commodities with Structural Breaks



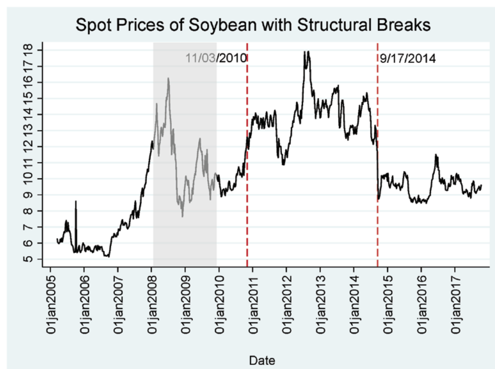
A. WTI Crude Oil



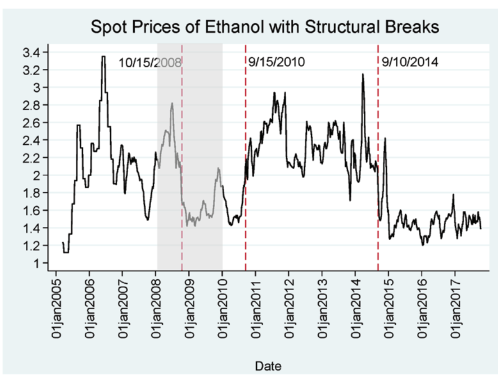
B. Natural Gas



C. Corn



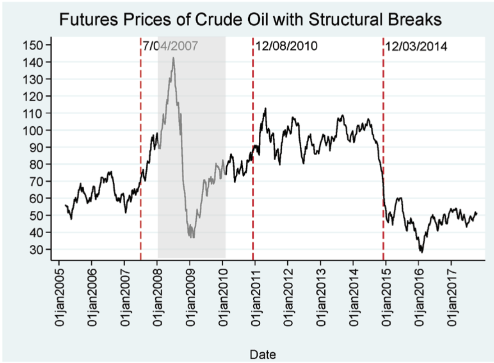
C. Soybean



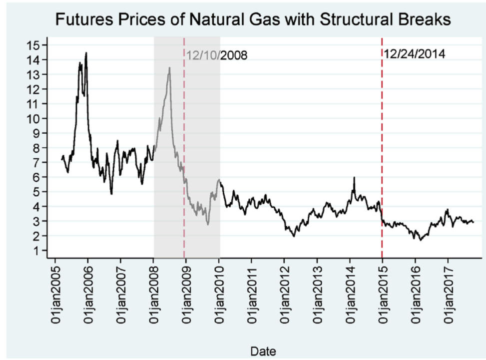
D. Ethanol

mean price of about \$5, its standard deviation was almost a half of the mean price, for both the spot and futures. The distributions of spot and futures prices also significantly deviated from normality, as suggested by the Jarque-Bera test statistics and the corresponding p-values. In addition, prices are positively skewed and leptokurtic. The skewness implies more volatile episodes in the prices, and the high-volatility episodes are more likely to occur than low-volatility episodes. The leptokurtosis implies that the distribution is more clustered around the mean and that extreme volatility movements are more likely to occur within the heavy tails relative to a normal distribution. Table 1 also shows the descriptive statistics of price returns for spot and futures. The minimum and maximum

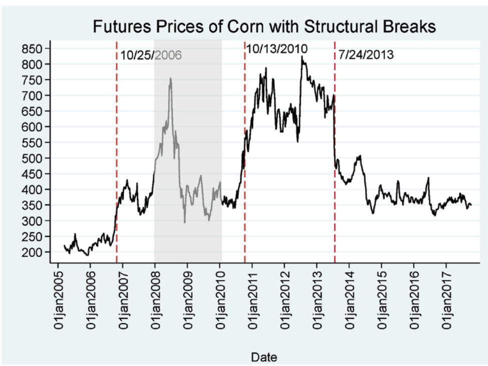
Figure 2: Futures Prices of Energy and Agricultural Commodities with Structural Breaks



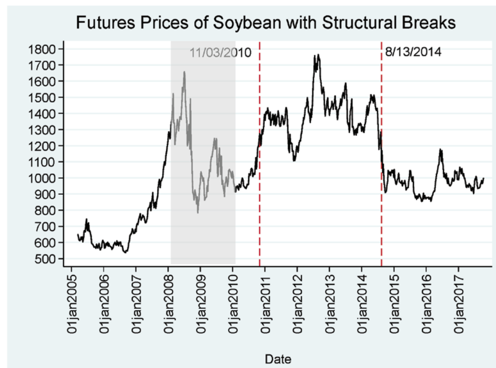
A. WTI Crude Oil



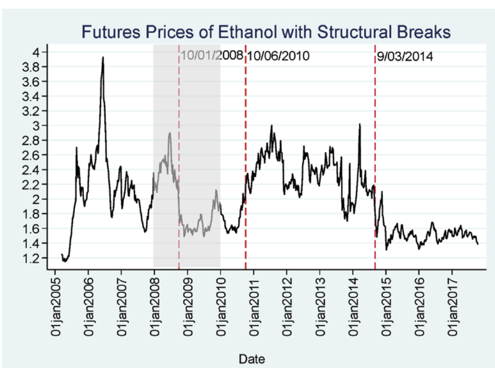
B. Natural Gas



C. Corn



C. Soybean



D. Ethanol

values show some very large weekly fluctuations in general, reflecting the fact that commodity prices are very volatile. Even though the average weekly absolute percentage price change for corn is about 3.4%, for example, the extremely weekly price swings could be as high as –81% (downswing) or 79% (upswing). The Jarque-Bera test statistics also reject the null hypothesis of normality in the returns of all commodities. Furthermore, descriptive statistics for the control variables are also listed in Table 1.

Based on the unit-root test proposed by Ng and Perron (2001) in Table 2, Panel A indicates that most of the price level variables show nonstationarity, with some of the unit roots

Table 1: Descriptive Statistics

Variable	Obs.	Mean	SD	Minimum	Max.	Skewness	Kurtosis	Jarque-Bera (*p*-values)
Spot Prices								
WTI Crude Oil	657	74.434	22.920	28.140	142.520	0.286	2.066	44.079(0.000)
Natural Gas	657	4.837	2.466	1.570	14.490	0.268	2.073	42.084(0.000)
Soybean	657	10.513	2.939	5.150	17.920	1.392	5.328	483.922(0.000)
Corn	657	4.280	1.613	1.680	8.410	0.320	2.336	23.342(0.000)
Ethanol	657	1.956	0.468	1.120	3.350	0.932	2.927	127.875(0.000)
Futures Prices								
WTI Crude Oil	657	74.526	22.847	28.150	142.460	0.863	2.808	110.927(0.000)
Natural Gas	657	4.904	2.498	1.687	14.462	0.281	2.066	43.653(0.000)
Soybean	657	1,065.146	288.295	537.000	1,764.500	0.598	3.242	40.825(0.000)
Corn	657	438.732	154.075	189.750	824.500	1.372	5.176	450.604(0.000)
Ethanol	657	1.987	0.459	1.150	3.930	0.227	2.023	42.650(0.000)
Spot Prices Returns								
WTI Crude Oil	657	–0.012	4.232	–19.100	25.125	–0.272	4.777	126.709(0.000)
Natural Gas	657	–0.139	6.677	–30.928	30.099	0.567	9.055	1,039.028(0.000)
Soybean	657	0.062	4.460	–44.338	45.982	0.548	11.973	2,999.693(0.000)
Corn	657	0.068	6.384	–81.357	79.004	–0.338	6.199	392.503(0.000)
Ethanol	657	0.010	4.752	–19.125	28.122	–0.520	31.564	2,990.390(0.000)
Futures Prices Returns								
WTI Crude Oil	657	–0.012	4.050	–18.723	15.527	–0.419	6.233	305.356(0.000)
Natural Gas	657	–0.138	5.517	–19.774	21.842	–0.815	11.641	2,116.583(0.000)
Soybean	657	0.062	3.935	–26.468	23.326	0.072	4.247	43.118(0.000)
Corn	657	0.069	4.428	–25.427	20.284	–0.266	4.837	100.146(0.000)
Ethanol	657	0.018	5.008	–32.980	31.319	–0.827	9.108	1,096.099(0.000)
Control Variables								
ΔWorld Crude Oil Stocks	657	0.091	1.122	–5.280	5.050	–0.054	4.357	50.69(0.000)
ΔU.S. Natural Gas Storages	657	0.138	4.092	–17.798	9.488	–1.050	4.026	149.50(0.000)
ΔInterest Rate Spread (=10-Year Treasure Bill—FED Fund Rate)	657	1.713	1.145	–0.788	3.754	–0.470	2.495	31.15(0.000)
ΔGlobal Real Economic Activity (Killian's Economic Index)	657	–0.671	3.947	–45.862	2.268	–9.506	105.849	300.01(0.000)
ΔTrade Weighted U.S. Dollar Index (Broad)	657	0.014	0.624	–2.983	3.334	0.261	5.738	212.61(0.000)

Data sources: The data used for our analysis are weekly prices for U.S. crude oil, natural gas, ethanol, corn, and soybean from March 15, 2005, through October 18, 2017. The spot oil price is the West Texas Intermediate crude oil FOB spot price obtained from the Energy Information Administration (EIA). The spot agricultural commodities are the No. 2 yellow corn FOB Gulf price and No. 1 yellow soybean, reported by the Food and Agriculture Organization (FAO). The spot natural gas price is the Henry Hub price obtained from EIA as well. The ethanol price is dollars per gasoline equivalent gallon (rack prices) collected from EIA. We also obtained the futures prices of the five commodities from the same respective sources. World crude oil stock and U.S. natural gas storage are obtained from EIA. We have collected the data on interest rate spreads (measured by 10-Year Treasure Bill minus Federal Funds Rate) and Trade Weighted U.S. Dollar Index (Broad) form Federal Reserve Bank of St. Louis (fred.stlouisfed.org). Global real economic activity (Killian's Economic Index) is obtained from the estimates by Killian (http://www-personal.umich.edu/~lkilian).

rejected at a very high significance level (1%), while the returns of the all variables were stationary. In addition, with the ARCH-LM tests, we find that there existed significant ARCH effects (Panel B), as we can reject the null hypothesis of no ARCH effect highly significantly. This justifies our use of conditional volatility models to model variances. Furthermore, prior to conducting our VAR estimation of the return variables, we determined the optimal VAR lag order using several criteria including LogL, sequential modified LR test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ). Table 3 indicates that 3 lags are the best for our spot and futures return VAR systems.

Table 2: Ng and Perron (2001) Unit Root Test and Conditional Heteroscedasticity Test

Panel A: Ng and Perron (2001) Unit Root Test (with an Intercept)

	Ng-Perron test statistics			
Variables	$MZ^{GLS}a$	$MZ^{GLS}t$	MSB^{GLS}	$MP^{GLS}t$
Level				
Spot Prices				
WTI Crude Oil	–2.804	–1.167	0.416*	8.688*
Natural Gas	–13.278**	–2.504**	0.189**	2.129**
Soybean	–3.471	–1.298	0.374*	7.057*
Corn	–2.244	–0.992	0.442*	10.435*
Ethanol	–7.835*	–1.979*	0.253**	3.127**
Futures Prices				
WTI Crude Oil	–2.722	–1.149	0.422*	8.940*
Natural Gas	–10.706**	–2.235**	0.209**	2.601**
Soybean	–2.758	–1.145	0.415*	8.787*
Corn	–2.414	–1.026	0.425*	9.745*
Ethanol	–5.892*	–1.715*	0.291*	4.162**
Returns				
Spot Prices				
WTI Crude Oil	–1.699	–0.794	0.167	1.251
Natural Gas	–0.018	–0.017	0.127	0.489
Soybean	–2.637	–1.112	0.122	0.915
Corn	–1.857	–0.930	0.101	1.277
Ethanol	0.202	0.567	0.180	1.141
Futures Prices				
WTI Crude Oil	–1.763	–0.821	0.166	1.227
Natural Gas	–0.636	–0.420	0.160	1.448
Soybean	0.340	0.873	0.034	0.057
Corn	0.035	0.074	0.039	0.078
Ethanol	0.219	0.437	0.039	0.076
Asymptotic critical values:				
1%	–13.8	–2.58	0.174	1.78
5%	–8.1	–1.98	0.233	3.17
10%	–5.7	–1.62	0.275	4.45

Panel B: Conditional heteroscedasticity test

Variables	*ARCH-LM* Tests
Returns	
Spot Prices	
WTI Crude Oil	49.43[a] (0.000)
Natural Gas	42.719[a] (0.000)
Soybean	102.893[a] (0.000)
Corn	40.110[a] (0.000)
Ethanol	7.797[a] (0.000)
Futures Prices	
WTI Crude Oil	18.737[a] (0.000)
Natural Gas	19.371[a] (0.000)
Soybean	28.883[a] (0.000)
Corn	14.424[a] (0.000)
Ethanol	1.162[a] (0.314)

Note: *, **, *** Means rejection of the null hypothesis of unit root at the 10%, 5%, and 1%, respectively. The order of lag to compute the tests has been chosen using the modified AIC (MAIC) suggested by Ng and Perron (2001).
[a] Denotes the rejection of the null hypotheses of normality, no autocorrelation, unit root, non-stationarity, and conditional homoscedasticity at the 1% significance level. The *P*-values are reported in the parentheses.

We estimated the DCC-MGARCH model for the spot and futures returns separately, and incorporated different regimes identified by structural breaks in our empirical specification of the model as in Equation 1 and Equation 2. In addition, to explore the possible cointegration of the price

Table 3: Selection Criteria of Optimal VAR Lag Order

# of Lag	LogL	LR	AIC	SC	HQ
Panel A: Returns on Spot Prices					
0	–5,948.63		19,613.93	18.40	18.42
1	–5,907.29	82.18	17,747.67	18.30	18.48
2	–5,898.50	17.37	17,759.66	18.30	18.44
3*	–5,888.17	20.34	17,686.82*	18.29*	18.40*
4	–5,883.47	9.21	17,923.58	18.31	18.58
5	–5,871.85	22.67	17,779.03	18.30	18.63
6	–5,863.79	15.64	17,831.19	18.30	18.70
7	–5,858.81	9.62	18,054.82	18.31	18.77
8	–5,857.39	2.73	18,483.60	18.34	18.86
9	–5,848.09	17.80	18,467.29	18.34	18.92
10	–5,845.24	5.43	18,822.87	18.36	19.00
Panel B. Returns on futures prices					
0	–7,550.74		6,845.46	17.34	17.47
1	–7,520.66	59.88	6,522.02	17.30	17.37
2	–7,510.00	21.14	6,554.31	17.30	17.41
3*	–7,504.81	10.27	6,497.29*	17.29*	17.36*
4	–7,493.27	22.73	6,516.26	17.30	17.51
5	–7,484.78	16.66	6,523.97	17.30	17.56
6	–7,481.59	6.24	6,611.62	17.31	17.62
7	–7,477.91	7.17	6,692.99	17.32	17.68
8	–7,469.03	17.25	6,694.93	17.32	17.73
9	–7,462.65	12.36	6,735.38	17.33	17.79
10	–7,460.55	4.04	6,843.22	17.34	17.85

Note: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion.

variables, we estimated an Error Correction Model (ECM) of the prices first and then incorporated the long-term disequilibrium terms from the cointegrated price variable system into the mean equation of the DCC-MGARCH model. In addition to the ECM term and the lagged return variables, we also incorporated control variables based on our previous discussions. Equation 2 defines our estimation of the conditional variance-covariances of the system, incorporating structural breaks as well into the variance equations. Table 4 reports the results using the spot prices and Table 5 reportd the results using the futures prices. Based on the estimation results of the DCC-MGARCH model, we then further examined the impulse responses of the price return of the five commodity variables to the one-standard deviation shocks in these variables. Finally, we completed the analysis by generating the dynamic volatility correlations between energy and agricultural commodities from our DCC-MGARCH model estimation.

5.2 The Cointegration Relation among Energy and Agricultural Commodity Prices

Before we estimated the DCC-MGARCH model, we estimated the cointegration of the price variables. We have restricted the number of the cointegration vector to be one as our focus here is on all five variables. The restricted cointegration vector obtained from spot prices is

$$\underset{(-2.323)}{-0.018\ \text{Oil Price}} - \underset{(-.593)}{0.001\ \text{Gas}} + \underset{(1.802)}{0.001\ \text{Corn}} + \underset{(2.896)}{0.004\ \text{Soybean}} + \underset{(4.329)}{0.001\ \text{Ethanol}} = 0$$

with numbers in parentheses being t-values. This suggests that except natural gas, other commodities maintained a positive long-term relationship with oil prices. This long-term relationship for the sample period appears to support the visual inspection of the price movement in each of the series in Figure 1, especially the price movement of crude oil, corn and soybean.

We obtained a very similar cointegration relationship from futures prices as shown below:

$$\begin{array}{lllll} -0.022\ \text{Oil Price} & -\ 0.000\ \text{Gas} & +\ 0.042\ \text{Corn} & +\ 0.274\ \text{Soybean} & +\ 0.001\ \text{Ethanol} = 0 \\ \quad(-3.206) & \quad(-0.461) & \quad(0.802) & \quad(2.441) & \quad(3.611) \end{array}$$

Please note that the magnitude differences in the coefficients of corn and soybean in the spot and futures cointegration relationships are due to the differences in the measuring units of both prices. Cash or spot price of corn/soybean is measured in dollars per bushel while the futures price is measured in cents per bushel. When estimated using the futures price, only soybean and ethanol prices were found to have a significant cointegrated relationship with the oil price. These results suggest there was a positive connection among the energy commodity and agricultural commodity prices: higher oil price was associated with higher corn, soybean and ethanol prices, or, there was a co-movement of these commodity prices (except natural gas) for the sample period.

5.3 Responding to Disequilibrium in Long-Term Price Relationship

Table 4 presents the estimation results of the DCC-MGARCH model using the spot price return data. Panel A in table 4 shows the estimation results of the mean equation which constitutes the effects from the disequilibrium from the cointegration relationship among the five variables, lagged return values, control variables as well as the food-crisis dummy and break dummies. The estimated coefficients on the ECM (long-term relationship) row show four significant estimated values, of which only the coefficients on corn and soybean have negative values, which suggests that corn and soybean prices responded to disequilibrium in the long-term relationship while oil price and ethanol prices did not. Natural gas price was not found to have any long-term relationship with the other variables so it naturally did not respond to any disequilibrium in the system of other four variables. This suggests a one-way impact of oil price and ethanol price to corn and soybean in the long term.

5.4 Short-Term Price Feedback Effect

The estimated coefficients to the lagged price return variables reveal how the return variables responded to their own lagged values and lagged values of other variables. These coefficients normally measure the short-term feedback effects of variables to each other. In the first column, there is only a couple of significant values associated with the lagged oil price returns. The positive summed value of the first two coefficients (0.214 and –0.114) suggests that there was a positive feedback effect of oil price returns to itself. As none of other lagged variables had any statistically significant estimates, oil price returns did not respond to other variables. In another word, oil price had some short-term positive feedback effect of its own and none of the other prices had any short-term price impact on the oil price.

The next four columns show the response patterns of natural gas, corn, soybean and ethanol. It appears that natural gas only responded to its own lagged values with a positive one-period feedback. Corn price had a negative feedback effect on its own while it had a positive feedback effect from both ethanol and natural gas but a negative feedback effect from oil and soybean. Soybean price was negatively affected by its own lagged values but positively affected by lagged ethanol price. Lastly, ethanol price responded to its own lagged value positively, also positively to oil, natural gas and corn prices, but negatively to soybean price.

Table 4: Estimation Results of the DCC-MGARCH Model: Returns on Spot Prices

Variables	ΔWTI Crude Oil	ΔNatural Gas	ΔCorn	ΔSoybean	ΔEthanol
Panel A: Conditional Mean Equation					
Constant	0.277(1.197)	0.275(0.702)	1.596***(5.196)	1.045***(4.710)	0.091(0.330)
ECM (Long-term Relationship)	0.001(0.523)	0.009***(5.460)	–0.026***(–36.725)	–0.009***(–9.877)	0.006***(4.411)
ΔWTI Crude Oil (t–1)	0.214***(5.156)	0.044(0.866)	–0.080**(–2.036)	–0.003(–0.093)	0.065**(2.060)
ΔWTI Crude Oil (t–2)	–0.114***(–2.636)	0.018(0.292)	–0.033(–0.771)	–0.010(–0.296)	–0.070**(–2.139)
ΔWTI Crude Oil (t–3)	–0.010(–0.240)	–0.029(–0.575)	0.025(0.637)	0.041(1.270)	0.061*(1.907)
ΔSoybean (t–1)	0.017(0.368)	0.094(1.305)	–0.045(–0.656)	–0.069(–1.243)	–0.076(–1.592)
ΔSoybean (t–2)	0.050(1.071)	–0.038(–0.526)	–0.064(–1.063)	–0.047(–0.901)	0.042(0.906)
ΔSoybean (t–3)	–0.002(–0.053)	0.038(0.515)	–0.260***(–4.303)	–0.160***(–3.118)	–0.090*(–1.958)
ΔNatural Gas (t–1)	–0.027(–1.394)	0.131***(2.874)	0.058**(2.201)	0.014(0.630)	–0.031(–1.475)
ΔNatural Gas(t–2)	0.022(1.137)	–0.034(–0.792)	0.021(0.843)	0.017(0.876)	0.046**(2.076)
ΔNatural Gas(t–3)	0.009(0.479)	–0.032(–0.791)	0.040(1.636)	–0.010(–0.482)	0.017(0.797)
ΔEthanol (t–1)	0.012(0.457)	0.080(1.609)	0.029(0.758)	0.032(1.000)	0.241***(5.406)
ΔEthanol (t–2)	0.017(0.646)	0.034(0.649)	0.024(0.633)	–0.018(–0.542)	–0.049(–1.076)
ΔEthanol (t–3)	0.008(0.299)	0.041(0.838)	0.108***(3.035)	0.074***(2.704)	0.010(0.240)
ΔCorn (t–1)	0.035(1.075)	0.042(0.759)	–0.169***(–2.876)	–0.038(–0.991)	0.231***(6.097)
ΔCorn (t–2)	–0.013(–0.375)	–0.053(–0.971)	–0.033(–0.582)	0.029(0.753)	0.026(0.682)
ΔCorn (t–3)	0.018(0.548)	0.061(1.100)	0.051(0.973)	0.079**(2.113)	0.067*(1.790)
Control Variables					
ΔWorld Crude Oil Stocks(t–1)	–0.183*(–1.660)				
ΔU.S. Natural Gas Storages(t–1)		0.088*(1.687)			
ΔInterest Rate Spread (=10-Year Treadure Bill – FED Fund Rate) (t–1)	–0.106(–0.944)	–0.175(–0.924)	–0.676***(–4.371)	–0.381***(–3.586)	–0.013(–0.104)
ΔGlobal Real Economic Activity (killian's Economic Index)(t–1)	–0.006(–0.194)	0.067*(1.885)	0.061(1.379)	0.051*(1.783)	–0.002(–0.044)
ΔTrade Weighted U.S. Dollar Index (Broad) (t–1)	–0.113(–0.437)	0.840**(2.207)	0.027(0.091)	0.309(1.273)	–0.234(–1.012)
Global Food Crisis Dummy (1, if year=2008~2009)	–0.268(–0.437)	–1.096(–1.605)	–0.583**(–1.986)	–1.416**(–2.518)	–0.578(–1.043)
Oil SB(Regime#1, Dummy=1, if period=July 4, 2007~December 8, 2010)	0.406(0.808)				
Oil SB (Regime#2, Dummy=1, if period=December 8, 2010~December 3, 2014)	–0.508(–1.416)				
Oil SB (Regime#3, Dummy=1, if period=December 3, 2014~October 18, 2017)	–0.409(–0.923)				
Natural Gas SB(Regime#1, Dummy=1, if period=December 10, 2008~December 24, 2014)		–0.566(–1.087)			
Natural Gas SB(Regime#2, Dummy=1, if period=December 24, 2014~October 18, 2017)		–0.757(–1.291)			
Corn SB(Regime#1, Dummy=1, if period=October 25, 2006~October 20, 2010)			–2.916***(–4.929)		
Corn SB(Regime#2, Dummy=1, if period=October 20, 2010~September 11, 2013)			–3.586***(–5.543)		
Corn SB(Regime#3, Dummy=1, if period=September 11, 2013~October 18, 2017)			–3.413***(–5.293)		
Soybean SB(Regime#1, Dummy=1, if period=November 3, 2010~September 17, 2014)				–1.249***(–3.357)	
Soybean SB(Regime#2, Dummy=1, if period=September 17, 2014, 2013~October 18, 2017)				–1.271***(–3.476)	
Ethanol SB(Regime#1, Dummy=1, if period=October 15, 2008~September 15, 2010)					–0.580(–1.427)
Ethanol SB(Regime#2, Dummy=1, if period=September 15, 2010~September 10, 2014)					–1.574***(–3.214)
Ethanol SB(Regime#3, Dummy=1, if period=September 10, 2014~October 18, 2017)					–1.241***(–2.616)

Note: Heteroskedasticity robust standard errors in parenthesis. ***, ** and * denote statistical significance at the 1, 5 and 10% level, respectively. *(continued)*

Table 4: Continued

Variables	ΔWTI Crude Oil	ΔNatural Gas	ΔCorn	ΔSoybean	ΔEthanol
Panel B: Conditional Mean Equation					
Constant	0.375**(2.077)	3.277***(3.259)	2.355***(3.404)	1.285***(3.775)	0.275**(2.275)
ARCH(t–1)	0.109***(5.118)	0.250***(5.197)	0.315***(5.928)	0.226***(5.763)	0.087***(5.000)
GARCH(t–1)	0.867***(33.939)	0.688***(13.752)	0.675***(14.262)	0.732***(20.287)	0.907***(58.788)
Global Food Crisis Dummy (1, if year=2008~2009)	0.534(0.959)	0.179(0.621)	0.663***(4.391)	0.182(1.257)	–0.550(–1.582)
Oil SB(Regime#1, Dummy=1, if period=July 4, 2007~December 8, 2010)	0.205(0.390)				
Oil SB (Regime#2, Dummy=1, if period=December 8, 2010~December 3, 2014)	–0.309(–0.874)				
Oil SB (Regime#3, Dummy=1, if period=December 3, 2014~October 18, 2017)	0.450(1.140)				
Natural Gas SB(Regime#1, Dummy=1, if period=December 10, 2008~December 24, 2014)		–0.348(–1.533)			
Natural Gas SB(Regime#2, Dummy=1, if period=December 24, 2014~October 18, 2017)		–0.625**(–2.210)			
Corn SB(Regime#1, Dummy=1, if period=October 25, 2006~October 20, 2010)			–3.046***(–14.374)		
Corn SB(Regime#2, Dummy=1, if period=October 20, 2010~September 11, 2013)			–3.284***(–15.977)		
Corn SB(Regime#3, Dummy=1, if period=September 11, 2013~October 18, 2017)			–2.869***(–13.785)		
Soybean SB(Regime#1, Dummy=1, if period=November 3, 2010~September 17, 2014)				–0.910***(–8.830)	
Soybean SB(Regime#2, Dummy=1, if period=September 17, 2014, 2013~October 18, 2017)				–1.302***(–10.039)	
Ethanol SB(Regime#1, Dummy=1, if period=October 15, 2008~September 15, 2010)					–1.139***(–3.138)
Ethanol SB(Regime#2, Dummy=1, if period=September 15, 2010~September 10, 2014)					–0.689***(–3.850)
Ethanol SB(Regime#3, Dummy=1, if period=September 10, 2014~October 18, 2017)					–0.956***(–3.957)
Correlation(Crude Oil, Soybean)	0.242***(4.609)				
Correlation (Crude Oil, Natural Gas)	0.149***(2.854)				
Correlation (Crude Oil, Ethanol)	0.210***(4.197)				
Correlation (Crude Oil, Corn)	0.196***(3.501)				
Correlation (Soybean, Natural Gas)	0.105*(1.888)				
Correlation (Soybean, Ethanol)	0.324***(6.342)				
Correlation (Soybean, Corn)	0.700***(25.406)				
Correlation (Natural Gas, Ethanol)	0.144***(2.758)				
Correlation (Natural Gas, Corn)	0.112*(1.924)				
Correlation (Ethanol, Corn)	0.352***(6.865)				
λ_1	0.004(1.061)				
λ_2	0.966***(80.246)				
Observations	654				
Log–likelihood Function	–8,530				
χ^2	153.5***				

Note: Heteroskedasticity robust standard errors in parenthesis. ***, ** and * denote statistical significance at the 1, 5 and 10% level, respectively.

These results concerning long-term and short-term price level interactions provide additional evidence to the claim that energy and agricultural commodity markets were connected at the price levels. Consistent with Trujillo-Barreva et al (2012) and Du et al (2011) which suggested a one-way connection from oil to corn, we do have some evidence to support that oil and gas prices were not influenced by agricultural commodities while agricultural commodities were largely influenced by energy commodities (both oil and gas). In addition, agricultural commodities and ethanol prices were interacting more within themselves while both oil and natural gas prices impacted ethanol price. In this sense, our empirical evidence suggests a transmission from energy commodities to agricultural commodities at the price level.

5.5 Effects of Control Variables on Prices

The second part in Panel A of Table 4 shows the effect of the control variables on the commodity prices. Oil inventory negatively affected the oil price return, which is consistent with conventional wisdoms. As inventories build up, market participants expect that more commodities are available for the future, thus the price drops as demand for oil declines due to market participants not going to build more inventories for the future. However, the estimated effect of gas inventory on gas price is positive. This result seems to contradict the findings of Chiou Wei et al (2014), but it can be consistent with the existence of gas market speculation. According to Frankel (2014), speculation can be defined as the behavior of market participants buying commodities in anticipation of price increase thus to gain at the time of sale. As inventories increase, market participants may interpret it as the signal that markets are building up inventories to prepare for future price increase, thus higher inventories would lead to further price increases as the result of building more inventories through purchases.

We find that the interest spread, as a proxy for credit condition or monetary policy, negatively affected the demand thus the prices of commodities. This is consistent with Frankel (2014) who suggested that monetary policy could have impacted the demand for commodities. As monetary policy tightens, bank lending reduces and some firms will issue more papers to finance their investment/spending. The cost of borrowing will increase as the spread becomes larger. Higher cost would raise the cost of holding commodity inventories thus reduce demand for commodities. However, this negative effect is not found universal in all the commodities and we are able to detect only two significantly negative relationships between price and the interest spread (corn and soybean) while no other commodities were found to be affected significantly by the interest spread.

The global economic activity appears to have statistically positive effects on two of the five commodities—natural gas and soybean. This evidence “half-heartedly” supports the proposition that economic growth increases demand for commodities which was cited as another reason for the co-movement in the commodity prices of 2000–2008 (Kilian and Hicks (2012). Others arguing against the economic growth leading to increases in commodity prices often cited the fact that commodity prices continued to increase in 2008 when the U.S. was already experiencing economic slowdown and the world economy was showing the sign of slowdown as well. Our evidence may be interpreted either as weakly supporting the hypothesis or refuting the hypothesis.

The relationship between the exchange rate (dollar value against other currencies) and commodity price can be complicated. One can argue for a positive relationship between the dollar value and commodity price with causations running both ways or argue both the exchange rate and commodity price can be affected by a common factor. Our empirical result does not provide any evidence of significant linkages between the value of the dollar and the commodity prices. The only case in which the coefficient of dollar exchange rate is significant is natural gas. As natural gas market is largely domestic, it is puzzling as to what the mechanism of the connections between these two variables would be.

The global food crisis of 2008–2009 caused policy makers, country leaders and agriculture market participants to try to understand the causes of the crisis (see for example, Gimenez (2008)). We tried to control for the effect of the crisis, however, the dummy variable also covers the period of commodity price collapse after the great recession. The significantly negative coefficients on corn and soybeans most likely do not reflect the effect of the food crisis. But unfortunately, there is no way we can disentangle the effect of food crisis from the effect of recession. One thing that may be worthy of noting is that the effects are only significant on two agricultural commodities rather than energy commodities. In this sense, the food crisis was more relevant to the agricultural commodities.

The last result reported in Panel A of Table 4 concerns the effects of the breaks detected in the series. For corn, soybean and ethanol prices, most of the breaks had some statistically negative effects on the prices. However, the interpretation of these negative effects is not clear except we do note that many of the breaks had occurred at the time of sharp price declines such as the end of 2014. So these results suggest that prices were transitioned to lower price regimes towards the end of the sample period.

5.6 Impulse Response Functions

The impulse response functions (IRFs) measure the response of variables to a one-standard deviation shock in its own shocks (own price shock effect) and to the shocks in each of the other variables (cross price shock effect) after controlling for exogenous variables and others such as lagged variables and dummies as in Equation 1. As price returns are all stationary, we would expect the IRFs to show temporary effects of the shocks. Figures 3–6 show the IRF of the variables. The cross-price shock effects are shown in Figure 3 (spot) and Figure 4 (futures) and own price shock effects are shown in Figure 5 (spot) and Figure 6 (futures).

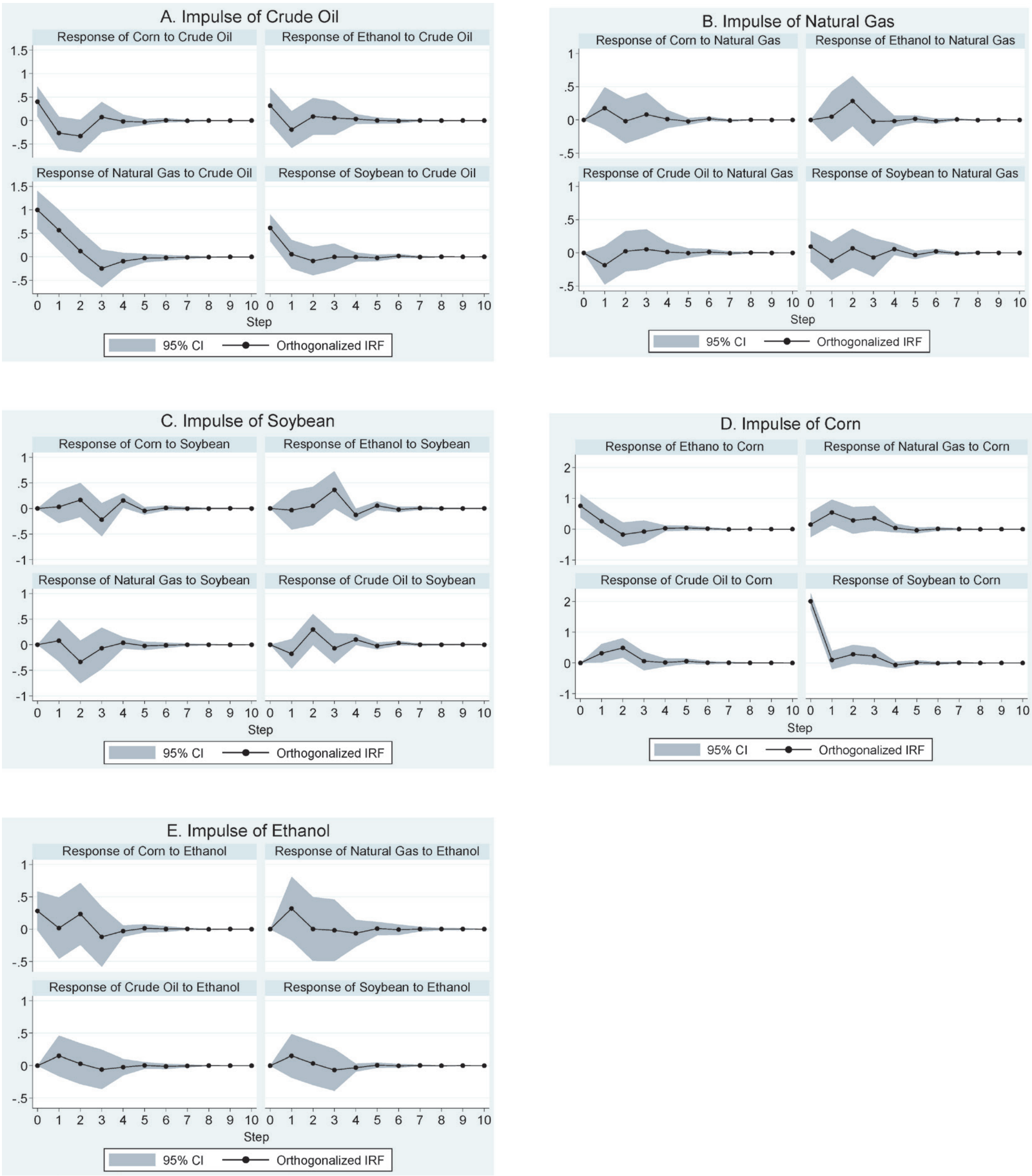
Most of the spot cross price effects are not very statistically significant except for natural gas price to shocks in oil and ethanol to shocks in corn which showed some very short-term positive effect at the lag of 1 week. The same can be said for these two pairs using futures prices. When using futures prices, surprisingly, all variables showed some significant one-week lagged response to shocks in ethanol prices. Looking at the own price effect, all variables responded to their own shocks positively with a one-period lag (either measured using the spot or futures prices). However, in general, these own price and cross price effect appeared to be relatively small and short-lived, suggesting very weak lagged price effect. However, the contemporaneous effects (at lag zero) of the shocks appeared to be bigger, especially in terms of the responses to shocks in oil price and ethanol, and corn (to a lesser degree).

5.7 The Conditional Volatility Estimation

Panel B of Table 4 shows the volatility estimation results of the five commodity price returns. Each of the models shows significant ARCH and GARCH effects. During the food crisis/ recession period, there were some significant increases in price volatility for corn, while volatility appeared to be higher but not statistically significant for other commodities.

Associating volatility changes with the structural breaks identified for each commodity, for most of the agricultural commodities, one can observe that both the period of 2010 to 2014 and the period after 2014 were associated with significantly lower volatilities, suggesting more stable

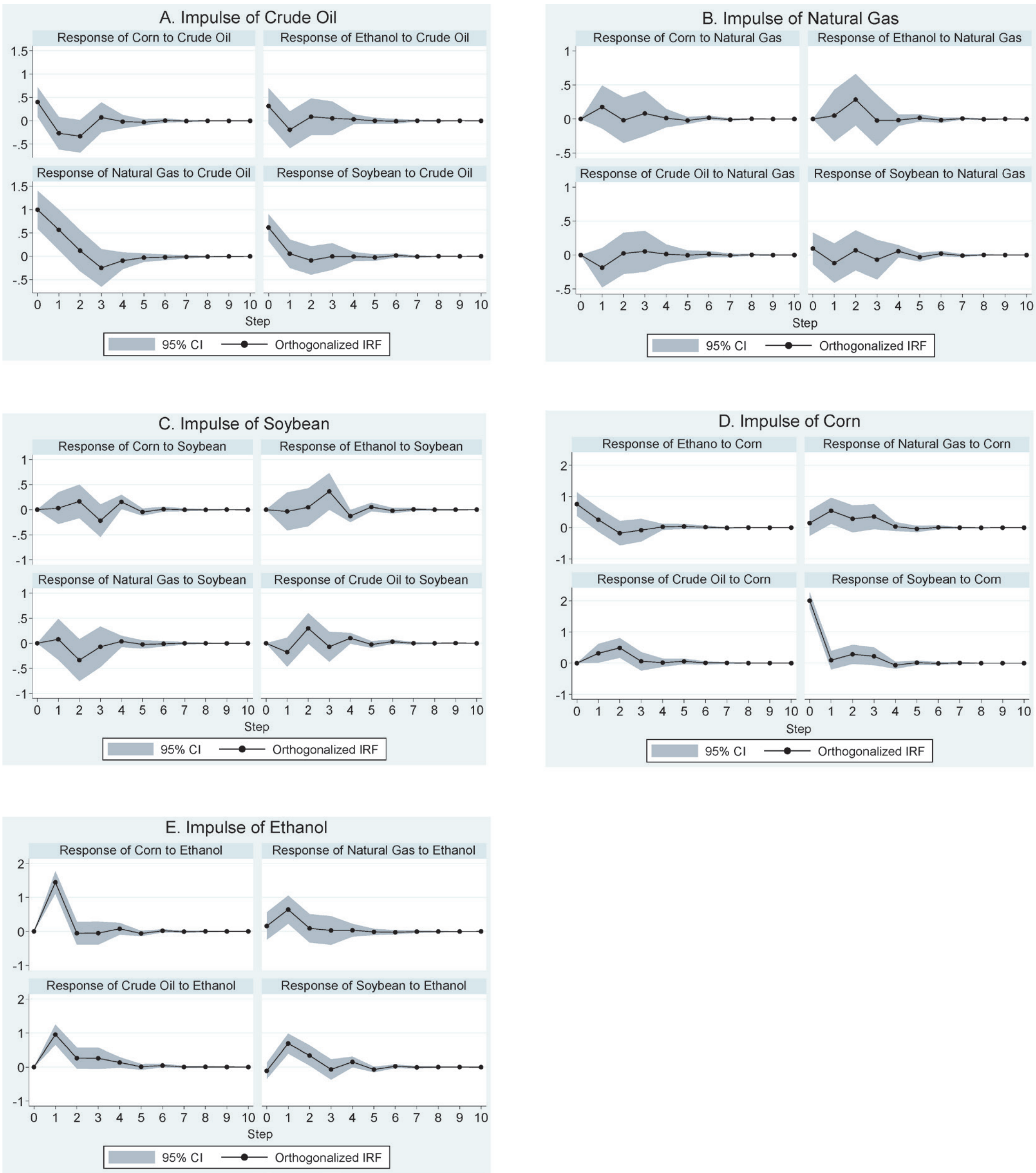
Figure 3: Impulse Responses of Spot Energy and Agricultural Commodity to the Shocks



markets for these commodities (corn, soybean, and ethanol) towards the end of the sample period. Combining with the result on the effect of the break dummies on price returns from Panel A, one can conclude that later regimes identified by the breaks had lower price returns as well as volatilities.

Panel B of Table 4 also shows the average correlation in conditional variances for different pairs of the commodities. While some values are rather small, all of them are statistically significant, suggesting that the volatilities in these markets were connected. However, magnitudes of the conditional volatility correlations are different dependent on commodity pairs. For example, the average conditional volatility correlation between soybean and corn is 0.70, suggesting a very high volatility connection between both agricultural commodities. On the other hand, natural gas seemed to be the

Figure 4: Impulse Responses of Futures Energy and Agricultural Commodity to the Shocks

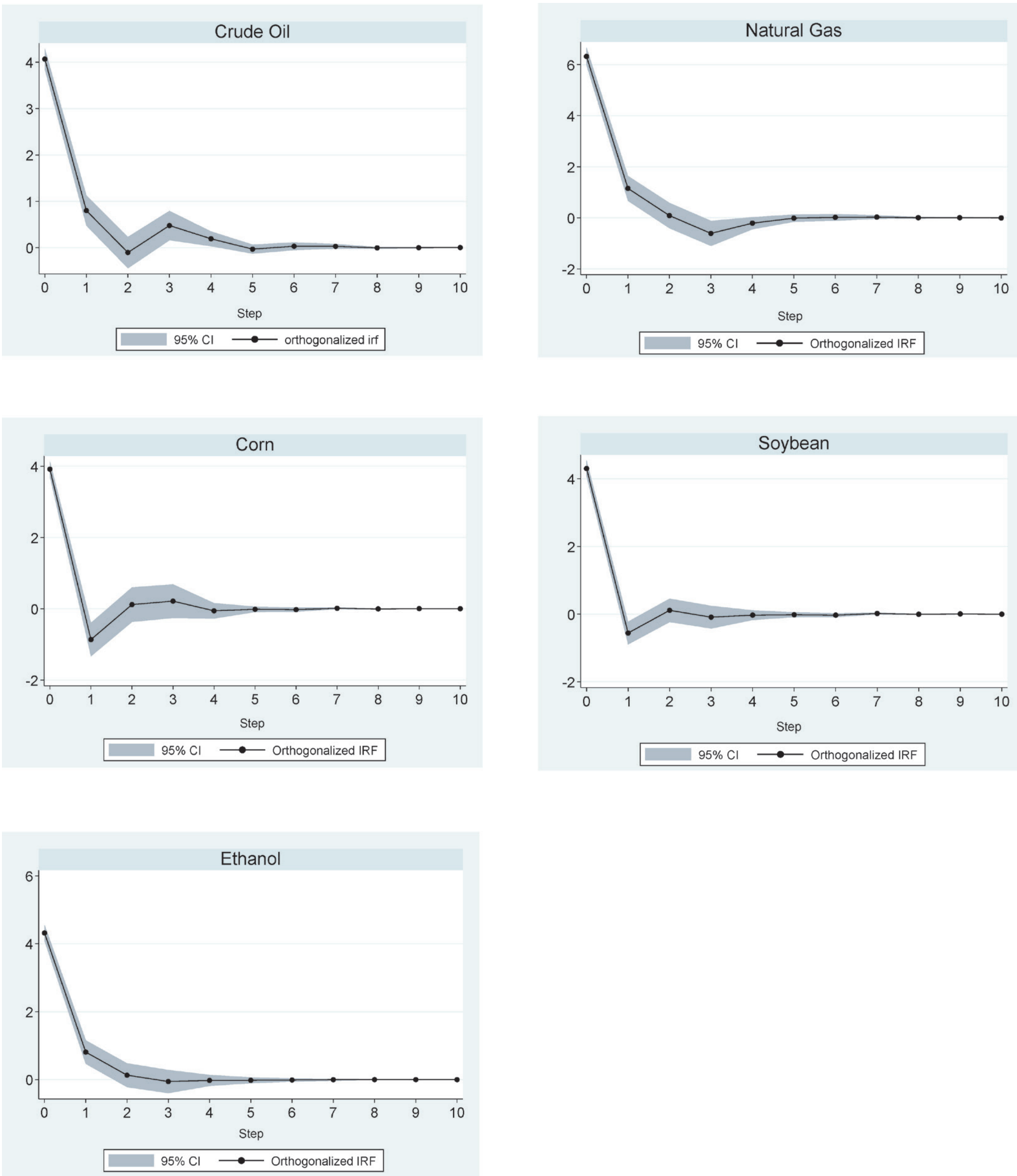


commodity that was more distant from the group of other commodities as its correlations with corn, soybean, ethanol, and oil are all relatively low (the lowest among the group). The next highest are the correlations between corn and ethanol, and soybean and ethanol. We will look at the patterns in the dynamic conditional correlation in Figure 7 in more detail.

5.8 Estimation Using Futures Price Data

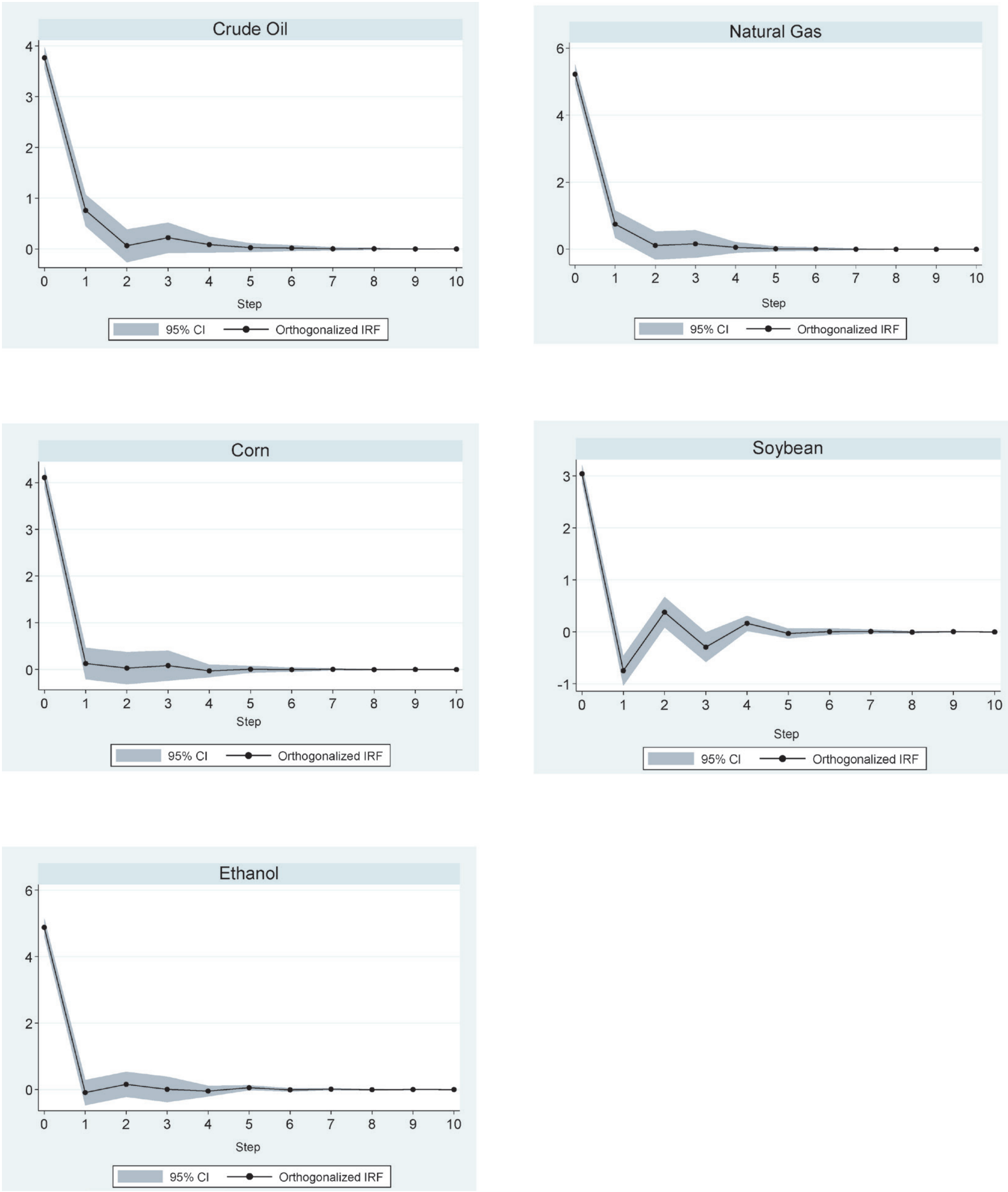
Estimations using futures price data have generated very similar results. In terms of the long-term relationships, oil, soybean, and ethanol prices were cointegrated but corn dropped out of the relationship compared to the spot price estimation result. Comparing Table 5 result to that

Figure 5: Impulse Responses of Spot Energy and Agricultural Commodity to Own Shocks



of Table 4, we observe similar patterns in the feedback effects of the lagged commodity variables on each of the other variables. Control variables now had less significant effects. While the interest spread variable still had a significantly negative effect on the agricultural commodities (corn and soybean), and the exchange effect on gas was still positive, we do not observe any evidence of world economic activity influencing the commodity markets. While the break dummy variables still had some significantly negative effects on returns, the negative effects of those breaks on volatilities were fewer, and the period of 2010 to 2014 generally saw some increases in volatilities in the corn, soybean, and ethanol markets. We also do not observe significant changes in the average values of

Figure 6: Impulse Responses of Futures Energy and Agricultural Commodity to Own Shocks

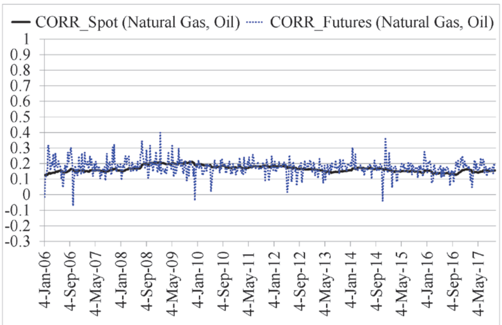


the conditional volatility correlations. The impulse response function analyses are also very similar to those obtained from the spot prices.

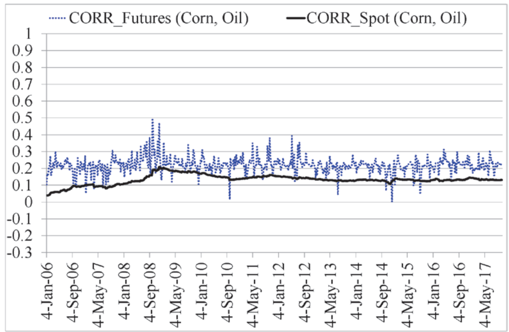
5.9 Dynamic Volatility Correlations among Energy and Agricultural Commodities

Figure 7 plots the estimated dynamic conditional correlations in volatility among the markets. Solid black line shows the estimated results using the spot price, and dashed blue line presents the results using futures price. Examination of these volatility correlations shows some distinctive patterns.

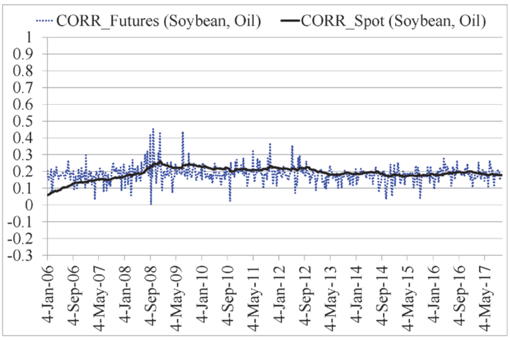
Figure 7: Dynamic Correlation between Energy and Commodity of Spot and Futures Prices Returns



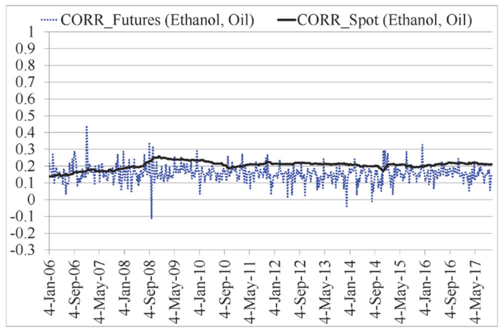
A. (Natural Gas, WTI Crude Oil)



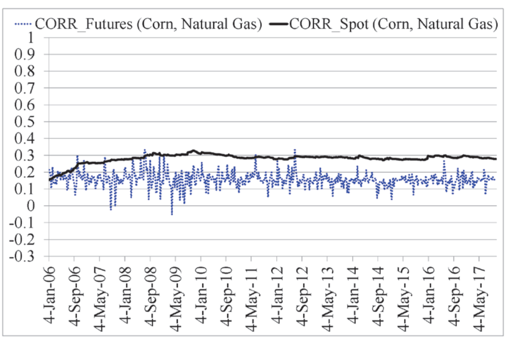
B. (Corn, WTI Crude Oil)



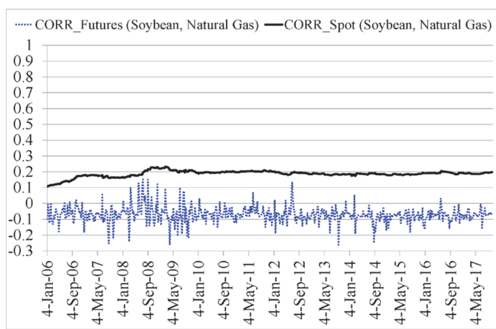
C. (Soybean, Oil)



D. (Ethanol, Oil)



E. (Corn, Natural Gas)

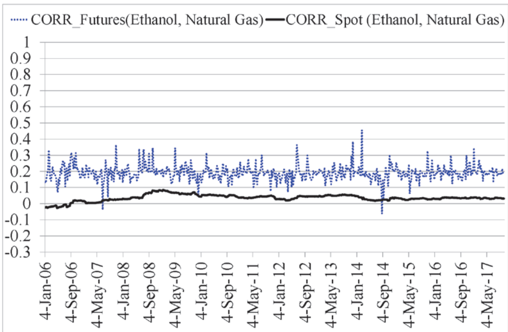


F. (Soybean, Natural Gas)

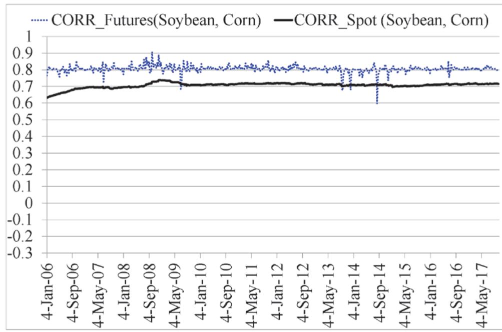
(continued)

One cannot help but to notice the rough lines for the volatility correlations derived from the futures price compared to those from the spot price. This suggests that the volatility correlation in the spot market was a lot more stable than the volatility correlation in the futures market. Even though our study will not be able to pinpoint the cause of this difference, one conjecture is that futures markets were more influenced by fast changing information flow to the market while spot markets might be less sensitive to those factors.

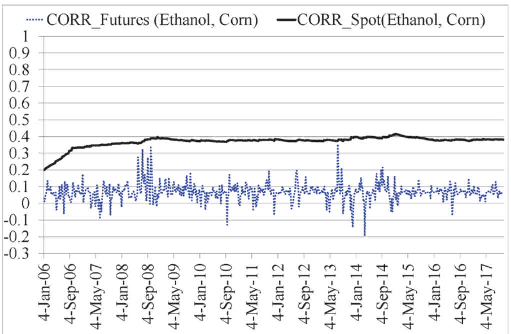
Figure 7: Continued



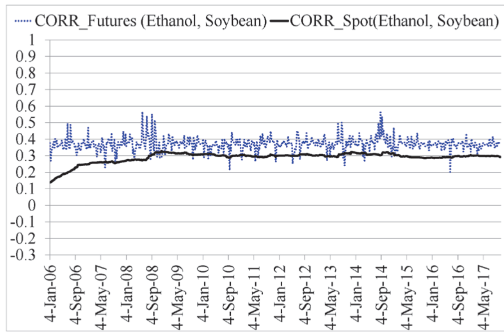
G. (Ethanol, Natural Gas)



H. (Soybean, Corn)



I. (Ethanol, Corn)



J. (Ethanol, Soybean)

We can also easily notice that correlations based on spot prices showed a pattern of general increase at the beginning of the sample period, reaching the peak around 2008/2009 and then staying roughly the same at the high level for the remaining sample period. There is no exception of commodities to this pattern. In comparison, the correlations based on futures prices fluctuated around an unobservable centerline, with correlations already at the high level at the beginning of the sample period. One possible explanation is that the increase in the correlation in the spot prices could be due to the feedback effect of the futures market on spot prices, considering the timing of the increase in the spot market volatility correlations.

Another major pattern found concerns the timing of some collective spikes in the correlations in the futures prices. We can observe that the correlations were generally the highest for all commodity pairs for the period of 2008 and 2009 during which commodity prices increased sharply and then followed by collapses. However, we do not observe similar volatility correlation patterns for the period of 2014 and 2015 when commodity prices experienced similar movements to those for the period of 2008 and 2009. Also we do not observe these spikes in spot prices. One could interpret this spike in volatility correlation in all commodity futures prices for 2008–2009 as related to possible speculations during the period. Provided that some co-movement may be caused by common economic variables, this unique pattern cannot be explained by common economic variables as we have already controlled for the effect of those variables. However, we caution that this explanation is largely of conjecture. More empirical studies are needed to ascertain the pattern and explain the pattern if the pattern is confirmed.

Table 5: Estimation Results of the DCC-MGARCH Model: Returns on Futures Prices

Variables	ΔWTI Crude Oil	ΔNatural Gas	ΔCorn	ΔSoybean	ΔEthanol
Panel A: Conditional Mean Equation					
Constant	0.171(0.757)	0.123(0.333)	0.413(1.526)	0.427**(2.123)	–0.295(–0.905)
ECM (Long-term Relationship)	0.003***(2.936)	0.015***(8.308)	–0.013***(–10.575)	0.010***(12.047)	–0.020***(–14.086)
ΔWTI Crude Oil (t–1)	0.209***(5.020)	0.044(0.839)	–0.096**(–2.453)	0.004(0.127)	–0.026(–0.654)
ΔWTI Crude Oil (t–2)	–0.068(–1.559)	0.040(0.710)	–0.057(–1.394)	–0.029(–0.873)	0.021(0.495)
ΔWTI Crude Oil (t–3)	–0.022(–0.520)	–0.083(–1.596)	0.027(0.679)	0.037(1.203)	–0.042(–1.044)
ΔSoybean (t–1)	0.008(0.194)	0.093(1.526)	0.026(0.469)	–0.142***(–2.897)	0.004(0.079)
ΔSoybean (t–2)	0.072*(1.673)	–0.057(–0.890)	0.041(0.910)	0.027(0.568)	–0.022(–0.411)
ΔSoybean (t–3)	–0.002(–0.044)	0.011(0.186)	–0.063(–1.413)	–0.033(–0.723)	0.093*(1.723)
ΔNatural Gas (t–1)	–0.024(–1.032)	0.109**(2.538)	0.045(1.628)	–0.002(–0.098)	0.021(0.668)
ΔNatural Gas(t–2)	0.020(0.890)	–0.027(–0.616)	0.019(0.657)	0.012(0.534)	0.066**(2.173)
ΔNatural Gas(t–3)	–0.007(–0.326)	0.013(0.312)	0.007(0.250)	–0.030(–1.474)	–0.011(–0.344)
ΔEthanol (t–1)	0.100***(4.237)	0.075*(1.950)	0.263***(7.948)	0.102***(4.370)	–0.043(–0.943)
ΔEthanol (t–2)	–0.000(–0.019)	–0.030(–0.709)	0.022(0.666)	0.048**(1.961)	–0.076(–1.596)
ΔEthanol (t–3)	0.015(0.650)	0.005(0.112)	0.026(0.804)	–0.009(–0.393)	–0.056(–1.159)
ΔCorn (t–1)	0.040(1.103)	0.074(1.339)	0.151624	0.043(1.230)	0.103**(1.998)
ΔCorn (t–2)	0.008(0.224)	0.030(0.543)	–0.079(–1.611)	0.002(0.056)	–0.014(–0.269)
ΔCorn (t–3)	0.003(0.084)	0.069(1.308)	0.042(0.866)	0.073**(2.068)	–0.066(–1.325)
Control Variables					
ΔWorld Crude Oil Stocks(t–1)	–0.141(–1.279)				
ΔU.S. Natural Gas Storages(t–1)		0.061(1.270)			
ΔInterest Rate Spread (=10-Year Treadure Bill—FED Fund Rate) (t–1)	–0.078(–0.704)	–0.143(–0.811)	–0.288**(–2.112)	–0.184*(–1.875)	0.059(0.366)
ΔGlobal Real Economic Activity (killian's Economic Index)(t–1)	–0.011(–0.341)	0.044(1.335)	0.024(0.644)	0.033(1.293)	–0.002(–0.050)
ΔTrade Weighted U.S. Dollar Index (Broad) (t–1)	–0.073(–0.290)	0.597*(1.686)	–0.124(–0.439)	0.197(0.899)	1.057351
Global Food Crisis Dummy (1, if year=2008~2009)	0.416(0.990)	0.068(0.116)	0.468(1.012)	0.317(0.779)	0.195(0.441)
Oil SB (Regime#1, Dummy=1, if period=July 4, 2007~December 8, 2010)	0.233(0.499)				
Oil SB (Regime#2, Dummy=1, if period=December 8, 2010~December 3, 2014)	–0.373(–1.071)				
Oil SB (Regime#3, Dummy=1, if period=December 3, 2014~October 18, 2017)	–0.161(–0.366)				
Natural Gas SB (Regime#1, Dummy=1, if period=December 10, 2008~December 24, 2014)		–0.24(–0.523)			
Natural Gas SB (Regime#2, Dummy=1, if period=December 24, 2014~October 18, 2017)		–0.097(–0.187)			
Corn SB (Regime#1, Dummy=1, if period=October 25, 2006~October 13, 2010)			–0.116(–0.649)		
Corn SB (Regime#2, Dummy=1, if period=October 13, 2010~July 24, 2013)			–1.180***(–3.243)		
Corn SB (Regime#3, Dummy=1, if period=July 24, 2013~October 18, 2017)			–0.439(–1.484)		
Soybean SB (Regime#1, Dummy=1, if period=November 3, 2010~August 13, 2014)				–0.651***(–2.841)	
Soybean SB (Regime#2, Dummy=1, if period=August 13, 2014~October 18, 2017)				–0.223(–1.114)	
Ethanol SB (Regime#1, Dummy=1, if period=October 1, 2008~October 6, 2010)					0.033(0.090)
Ethanol SB (Regime#2, Dummy=1, if period=October 6, 2010~September 3, 2014)					–0.345(–0.741)
Ethanol SB (Regime#3, Dummy=1, if period=September 3, 2014~October 18, 2017)					–0.383(–0.936)

Note: Heteroskedasticity robust standard errors in parenthesis. ***, ** and * denote statistical significance at the 1, 5 and 10% level, respectively.

(continued)

Table 5: Continued

Variables	ΔWTI Crude Oil	ΔNatural Gas	ΔCorn	ΔSoybean	ΔEthanol
Panel B: Conditional Mean Equation					
Constant	0.343**(2.010)	1.917***(2.633)	4.777***(3.413)	1.852***(3.012)	0.375*(1.658)
ARCH(t–1)	0.100***(4.569)	0.149***(4.081)	0.213***(3.236)	0.272***(4.738)	0.110***(4.221)
GARCH(t–1)	0.874***(31.963)	0.792***(18.772)	0.520***(4.955)	0.586***(6.710)	0.886***(36.901)
Global Food Crisis Dummy (1, if year=2008~2009)	0.453(0.935)	0.251(1.256)	0.855***(5.546)	1.231***(8.389)	0.107(0.502)
Oil SB (Regime#1, Dummy=1, if period=July 4, 2007~December 8, 2010)	0.208(0.448)				
Oil SB (Regime#2, Dummy=1, if period=December 8, 2010~December 3, 2014)	–0.195(–0.567)				
Oil SB (Regime#3, Dummy=1, if period=December 3, 2014~October 18, 2017)	0.547(1.433)				
Natural Gas SB (Regime#1, Dummy=1, if period=December 10, 2008~December 24, 2014)		0.033(0.197)			
Natural Gas SB (Regime#2, Dummy=1, if period=December 24, 2014~October 18, 2017)		–0.479**(–2.438)			
Corn SB (Regime#1, Dummy=1, if period=October 25, 2006~October 13, 2010)			0.230**(2.133)		
Corn SB (Regime#2, Dummy=1, if period=October 13, 2010~July 24, 2013)			0.780***(5.760)		
Corn SB (Regime#3, Dummy=1, if period=July 24, 2013~October 18, 2017)			–0.340***(–2.694)		
Soybean SB (Regime#1, Dummy=1, if period=November 3, 2010~August 13, 2014)				0.443***(4.020)	
Soybean SB (Regime#2, Dummy=1, if period=August 13, 2014~October 18, 2017)				–0.526***(–4.871)	
Ethanol SB (Regime#1, Dummy=1, if period=October 1, 2008~October 6, 2010)					–0.756***(–3.810)
Ethanol SB (Regime#2, Dummy=1, if period=October 6, 2010~September 3, 2014)					0.329**(2.117)
Ethanol SB (Regime#3, Dummy=1, if period=September 3, 2014~October 18, 2017)					–0.903***(–5.758)
Correlation(Crude Oil, Soybean)	0.184***(4.388)				
Correlation (Crude Oil, Natural Gas)	0.185***(4.552)				
Correlation (Crude Oil, Ethanol)	0.171***(4.202)				
Correlation (Crude Oil, Corn)	0.218***(5.308)				
Correlation (Soybean, Natural Gas)	–0.086**(–1.996)				
Correlation (Soybean, Ethanol)	0.397***(10.797)				
Correlation (Soybean, Corn)	0.854***(72.742)				
Correlation (Natural Gas, Ethanol)	0.189***(4.638)				
Correlation (Natural Gas, Corn)	0.143***(3.404)				
Correlation (Ethanol, Corn)	0.092**(2.149)				
λ_1	0.008*(1.886)				
λ_2	0.960***(69.655)				
Observations	654				
Log–likelihood Function	–9,035				
χ^2	272.1***				

Note: Heteroskedasticity robust standard errors in parenthesis. ***, ** and * denote statistical significance at the 1, 5 and 10% level, respectively.

In terms of the magnitude of the volatility correlation, it is the agricultural commodities (corn and soybean) and ethanol that showed the largest connections amongst themselves. The connections between energy and agricultural commodities did not seem to be very high, indicating relatively low volatility spillovers from one market to another in general. One puzzling pattern though is the different correlations for the same pair of commodities that exist for spot price and for futures price. For example, the volatility correlation between ethanol and corn was much higher for the spot market than for the futures market. The same is true for the pair of soybean and natural gas, corn and natural gas, and the opposite for ethanol and natural gas.

6. CONCLUSION AND POLICY IMPLICATIONS

6.1 Concluding Remarks

In this paper, we studied the connections between two energy commodities (oil and gas) and two agricultural commodities (corn and soybean) with ethanol as a commodity in between the two groups. The study is motivated by the internal connections amongst the commodities and the lack of empirical studies that directly link these five commodities, especially for a more recent period. Further, the study of these commodities can be justified by some external linkages among them. To be specific, our study can be justified by the fact that these commodities are influenced by some common economic variables, connected through economic policies (especially ethanol policies), production process, and demand substitutions.

We employed a dynamic conditional correlation (DCC) multivariate GARCH model to examine the connections between the five commodity prices at both the price (return) level and volatility level. We revealed some significant empirical regularities (or lack of empirical regularities). We find there was a long-term equilibrium relationship between oil, corn, soybean, and ethanol prices while natural gas seemed to stay out of these four-commodity group with respect to the long-term price connections. The finding of a long-term relationship is different from Zhang et al (2009) even though his study was in a slightly different commodity setting. When there was a disequilibrium in the long-term relationship, it was the agricultural commodities (corn and soybean) that would respond to the disequilibrium in the system. In terms of the short-term effect, our estimated short-term feedback effects (own and cross price effects) and the impulse response analysis suggest that agricultural commodities were often the ones that were influenced by other commodities. In this sense, our empirical evidence suggests that the direction of the impacts appeared to be more from energy commodities (especially oil) to agricultural commodities. This result appears to be consistent with those of Trujillo-Barrera et all (2012), Wu et al (2011), Du et al (2011), Harri and Darren (2009).

One of the innovations of our study is to incorporate economic variables in the model estimation so we can isolate out the effects of those common economic variables. Our estimation results reveal some result consistent with previous findings such as the negative effect of oil inventory on oil prices and the negative effect of interest spread on agricultural commodities. This result is more or less consistent with Frankel (2014). We find weak evidence of economic activity and exchange rate on commodities prices for this sample period. Furthermore, the impact of natural gas inventory on natural gas price may be suggestive of speculation in the gas market. However, this evidence is indirect and inclusive to say the most.

We also investigated the volatility connections among the five commodities. Our results suggest that there were statistically significant volatility correlations among the five markets. In general, agricultural commodity markets and ethanol market had the highest volatility connection while natural gas market had the lowest connection with the other markets. This result is consistent with the fact that economic policy promoted more connections between oil, ethanol, corn, and soybean (Thompson et al (2009)). Furthermore, our volatility correlation analysis provided a strong evidence of time-varying or dynamic conditional correlations in the volatilities. We have uncovered several interesting patterns. However, further studies are needed to confirm these patterns and provide plausible explanations for these patterns. In addition, our study only focused on spot markets or futures market as a group without investigating the spot and futures market interactions at the same time. While looking at the spot and futures markets at the same time does not fit into our current design and is not the objective of the study, it would be interesting to examine the interaction of the futures and spot prices as well. It may reveal more interesting findings of how spot and futures prices would interact in the markets environment since 2000, and it may also provide some additional evidence regarding the feedback effect of Socken and Xiong (2015). Future studies are needed in this direction.

In general, our empirical results appear to suggest that the connections among the markets were relatively weak more recently, as compared to early studies. The interactions in terms of the feedback effects in the price levels and in terms of the volatility connections were generally low. In additional, there is evidence to suggest that volatilities in these markets were getting lower especially for the agricultural commodity market and ethanol market. Lack of strong interactions and co-movement among the prices for the sample period may be indicative of lack of strong speculation-driven price movement and volatility.

6.2 Policy Implications

Our study provides some policy implications. As the evidence shows that the markets were still interconnected, policy makers need to consider all markets at the same time when designing policy for a single market. However, the time-varying nature of the connections and interactions among the markets suggests that policy makers should also be aware that the intermarket connections vary over time, so policies should be designed to address an issue at a particular time period by considering specific market conditions at the time.

Our empirical results also point to a closer connection between oil and agricultural commodity markets alongside ethanol. One plausible explanation is that this is due to the biofuel policy, as natural gas, also can be a feedstock in agricultural commodities, did not seem to have the same kind of effects as oil had on the agricultural commodities. Thus, policy makers need to be carefully with biofuel policies in order to minimize the negative effect of these policies on the price of agricultural commodities.

We also uncovered some support for speculation in the commodity market especially the natural gas market. Further studies are needed to confirm this effect and whether similar evidence can be obtained from the other markets. However, policy makers need to pay special attention to the speculation activities as some of the speculation activities may be destabilizing.

In addition, our results suggest some relatively low level of connections among the markets and reduced volatility in the agricultural commodity prices. This may help to release the pressure faced by the policy makers in making policies that address interconnections among the market.

To individual financial investors as well as commodity market participants, our results suggest that they need to be careful about the design of their financial diversification programs as these commodity markets are still interconnected, not only at the price level, but also at the volatility level. The direction of the interactions (natural gas market being largely separately from the rest of the block, and agricultural commodities and ethanol having more interactions) should help them to devise better strategies in their risk management and trading. The reduced level of volatility and interconnection might also have made it easier for the risk management programs. However, these results need to be confirmed by more studies.

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REFERENCES

Baele, L. (2005). "Volatility Spillover Effects in European Equity Markets: Evidence from a Regime Switching Model." *Journal of Financial and Quantitative Analysis* 40: 373–401. https://doi.org/10.1017/S0022109000002350.

Baffes, J. (2011). "The Energy/Non-Energy Price Link: Channels, Issues, and Implications." In *Methods to Analyze Agricultural Commodity Price Volatility,* I. Piot-Lepetit, ed. New York: Springer: 31–44. https://doi.org/10.1007/978-1-4419-7634-5_3.

Bai, J. and P. Perron (2003). "Computation and Analysis of Multiple Structural Change Models." *Journal of Applied Econometrics* 18(1): 1–22. https://doi.org/10.1002/jae.659.

Bekaert, G, C.R. Harvey, and A. Ng (2005). "Market Integration and Contagion." *Journal of Business* 78: 39–69. https://doi.org/10.1086/426519.

Bekaert, G., and C.R. Harvey (1997). "Emerging Equity Market Volatility." *Journal of Financial Economics* 43: 29–77. https://doi.org/10.1016/S0304-405X(96)00889-6.

Cabrer, B.L. and F. Schulz (2016). "Volatility Linkages between Energy and Agricultural Commodity Prices." *Energy Economics* 54: 190–203. https://doi.org/10.1016/j.eneco.2015.11.018.

Cevik, S. and T.S. Sedik (2011). "A Barrel of Oil or a Bottle of Wine: How Do Global Growth Dynamics Affect Commodity Prices?" Working Paper 11/01, International Monetary Fund.

Cheng, I.H. and W. Xiong (2014). "The Financialization of Commodity Markets." *Annual Review of Financial Economics* 6: 419–41. https://doi: 10.1146/annurev-financial-110613-034432.

Chiou-Wei, S.Z., S. Linn, and Z. Zhu (2014). "The Response of U.S. Natural Gas Futures and Spot Prices to Storage Change Surprises: Fundamental Information and the Effect of Escalating Physical Gas Production." *Journal of International Money and Finance* 42: 156–173. https://doi.org/10.1016/j.jimonfin.2013.08.009.

Christiansen, C. (2007). "Volatility-Spillover Effects in European Bond Markets." *European Financial Management* 13: 923–48. https://doi.org/10.1111/j.1468-036X.2007.00403.x.

de Gorter, H., D.R. Just, and K.D. Jaclyn (2008). "Cross-Subsidization Due to Infra-Marginal Support in Agriculture: A General Theory and Empirical Evidence." *American Journal of Agricultural Economics* 90: 45–54. https://doi.org/10.1111/j.1467-8276.2007.01044.x.

Du, X., C.L. Yu and D.J. Hayes (2011). "Speculation and Volatility Spillover in the Crude Oil and Agricultural Commodity Markets: A Bayesian Analysis." *Energy Economics* 33: 497–503. https://doi.org/10.1016/j.eneco.2010.12.015

Engle, R. and F.K. Kroner (1995). "Multivariate Simultaneous Generalized ARCH." Economic Theory 11: 122–150. https://doi.org/10.1017/S0266466600009063

Frankel, J.A. (2014). "Effects of Speculation and Interest Rates in a "Carry Trade" Model of Commodity Prices." *Journal of International Money and Finance* 42: 88–112. https://doi.org/10.1016/j.jimonfin.2013.08.006.

Gardebroek, C., and M.A. Hernandez (2013). "Do Energy Prices Stimulate Food Price Volatility? Examining Volatility Transmission between U.S. Oil, Ethanol and Corn Markets." *Energy Economics* 40: 119–129. https://doi.org/10.1016/j.eneco.2013.06.013

Gilbert, C.L., and C.W. Morgan (2010). "Food Price Volatility. Philosophical Transactions of the Royal Society of London." *Series B, Biological Sciences* 365: 3023–3034. https://doi.org/10.12691/jfe-5-3-1.

Gilbert, C.L. (2010). "How to Understand High Food Prices." *Journal of Agricultural Economics* 61 (2): 398–425. https://doi.org/10.1111/j.1477-9552.2010.00248.x.

Gimenez, E.H. (2008). "The World Food Crisis: What Is Behind It and What We Can Do?" https://www.worldhunger.org/world-food-crisis/.

Gozgor, G., and B. Kablamaci (2014). "The Linkages between Oil and Agricultural Commodity Prices in the Light of the Perceived Global Risk." *Agricultural Economics—Czech* 60 (7): 332–42. https://doi.org/10.17221/183/2013-AGRICECON.

Gozgor, G. and C. Memis (2015). "Price Volatility Spillovers among Agricultural Commodity and Crude Oil Markets: Evidence from the Range-Based Estimator." *Agricultural Economics* 61: 214–21. https://doi.org/10.17221/162/2014-AGRICECON.

Gozgor, G., C.K.M. Lau, and M.H. Bilgin (2016). "Commodity Markets Volatility Transmission: Role of Risk Perceptions and Uncertainty in Financial Markets." *Journal of International Financial Markets, Institutions & Money* 44: 35–45. https://doi.org/10.1016/j.intfin.2016.04.008.

Harri, A., and H. Darren (2009). "Mean and Variance Dynamics between Agricultural Commodity Prices and Crude Oil Prices and Implications for Hedging." In *The Economics of Alternative Energy Sources and Globalization: The Road Ahead Meeting*, Orlando, FL.

Henderson, B.J., N.D. Pearson, and L. Wang (2015). "New Evidence on the Financialization of Commodity Markets." *Review of Financial Studies* 28(5): 1285–311. https://doi.org/10.1093/rfs/hhu091.

Hertel, T., and J. Beckman (2011). "Commodity Price Volatility in the Biofuel Era: An Examination of the Linkage between Energy and Agricultural Markets." GTAP Working Papers 3214, Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University, West Lafayette, IN. https://doi.org/10.3386/w16824.

Irwin, S.H., and D.L. Good (2009). "Market Instability in a New Era of Corn, Soybean, and Wheat Prices." *Choices* 24: 7–11.

Kilian, L., and B. Hicks (2013). "Did Unexpectedly Strong Economic Growth Cause the Oil Price Shock of 2003–2008?" *Journal of Forecasting* 32(5): 385–94. https://doi.org/10.1002/for.2243.

Knittel, C.R. and R.S. Pindyck (2016). "The Simple Economics of Commodity Price Speculation." *American Economic Journal: Macroeconomics* 8(2): 85–110. https://doi.org/10.1257/mac.20140033.

Meyer, S. and W. Thompson (2010). "Demand Behavior and Commodity Price Volatility under Evolving Biofuel Markets and Policies." In *Handbook of Bioenergy Economics and Policy. Natural Resource Management and Policy,* M. Khanna, J. Scheffran, and D. Zilberman, eds., , Vol. 33. Springer Science, New York, 133–148. https://doi.org/10.1007/978-1-4419-0369-3_9.

Muhammad, A. and E. Kebede (2009). "The Emergence of an Agro-Energy Sector: Is Agriculture Importing Instability from the Oil Sector?" *Choices* 24: 12–15.

Nazlioglu, S., C. Erdem, and U. Soytas (2013). "Volatility Spillover between Oil and Agricultural Commodity Markets." *Energy Economics* 36: 658–665. https://doi.org/10.1016/j.eneco.2012.11.009.

Ng, S. and P. Perron (2001). "Lag Selection and the Construction of Unit Root Tests with Good Size and Power." *Econometrica* 69: 1519–54. https://doi.org/10.1111/1468-0262.00256.

Ridler, D. and C. A. Yandle (1972). "A Simplified Method for Analyzing the Effects of Exchange Rate Changes on Exports of A Primary Commodity." *IMF Staff Papers* 19: 559–578. https://doi.org/10.2307/3866417.

Serra, T. (2011). "Volatility Spillovers between Food and Energy Markets: A Semiparametric Approach." *Energy Economics* 33: 1155–64. https://doi.org/10.1016/j.eneco.2011.04.003.

Serra, T. and D. Zilberman (2013). "Biofuel-Related Price Transmission Literature: A Review." *Energy Economics* 37: 141–51. https://doi.org/10.1016/j.eneco.2013.02.014.

Serra, T., D. Zilberman, and J.M. Gil (2011). "Price Volatility in Ethanol Markets." *European Review of Agricultural Economics* 38: 259–80. https://doi.org/10.1093/erae/jbq046.

Sockin, M. and W. Xiong (2015). "Informational Frictions and Commodity Markets." *Journal of Finance* 70(5): 2063–98. https://doi.org/10.1111/jofi.12261.

Sorda, G., M. Banse, and C. Kemfert (2010). "An Overview of Biofuel Policies across the World." *Energy Policy* 38: 6977–88. https://doi.org/10.1016/j.enpol.2010.06.066.

Thompson, W., S. Meyer, and P. Westhoff (2009). "How Does Petroleum Price and Corn Yield Volatility Affect Ethanol Markets with and without an Ethanol Use Mandate?" *Energy Policy* 37: 745–9. https://doi.org/10.1016/j.enpol.2008.08.035.

Trujillo-Barrera, A., M. Mallory, and P. Garcia (2012). "Volatility Spillovers in U.S. Crude Oil, Ethanol, and Corn Futures Markets." *Journal of Agricultural and Resource Economics* 37(2): 247–62. http://www.jstor.org/stable/23496711.

Tyner, W.E. (2008). "The U.S. Ethanol and Biofuels Boom: Its Origins, Current Status, and Future Prospects." *BioScience* 58: 646–653. https://doi.org/10.1641/B580718.

Whistance, J., and W. Thompson (2009). "How Does Increased Corn-Ethanol Production Affect U.S. Natural Gas Prices?" *Energy Policy* 38: 2315–25. https://doi.org/10.1016/j.enpol.2009.12.019.

Whistance, J., W.W. Thompson, and S.D. Meyer (2010). "Ethanol Policy Effects on U.S. Natural Gas Prices and Quantities." *American Economic Review* 100: 178–82. http://www.jstor.org/stable/27804985. https://doi.org/10.1257/aer.100.2.178.

Wu, F., Z. Guan, and R.J. Myers (2011). "Volatility Spillover Effects and Cross Hedging in Corn and Crude Oil Futures." *Journal of Futures Markets* 31(11): 1052–75. https://doi.org/10.1002/fut.20499.

Yano, Y., D. Blandford, and Y.R. Surry (2010). "The Impact of Feedstock Supply and Petroleum Price Variability on Domestic Biofuel and Feedstock Markets—The Case of the United States." Working Paper 58486, Swedish University of Agricultural Sciences, Department of Economics.

Zhang, Z., L. Lohr, C. Escalante, and M. Wetzstein (2009). "Ethanol, Corn, and Soybean Price Relations in a Volatile Vehicle-Fuels Market." *Energies* 2: 320–39. http://doi:10.3390/en20200320.