Volatility Spillovers for Spot, Futures, and ETF Prices in Energy and Agriculture*

EI2016-28

Chia-Lin Chang
Department of Applied Economics
Department of Finance
National Chung Hsing University
Taiwan

Chia-Ping Liu
Department of Quantitative Finance
National Tsing Hua University
Taiwan

Michael McAleer
Department of Quantitative Finance
National Tsing Hua University
Taiwan
and
Econometric Institute
Erasmus School of Economics
Erasmus University Rotterdam
and
Department of Quantitative Economics
Complutense University of Madrid

Revised: June, 2016

* The authors are grateful to Leh-Chyan So for helpful comments and suggestions. For financial support, the first author wishes to thank the National Science Council, Taiwan, and the third author acknowledges the Australian Research Council and the National Science Council, Taiwan.

Abstract

The agricultural and energy industries are closely related, both biologically and financially. The paper discusses the relationship and the interactions on price and volatility, with special focus on the covolatility spillover effects for these two industries. The interaction and covolatility spillovers, or the delayed effect of a returns shock in one asset on the subsequent volatility or covolatility in another asset, between the energy and agricultural industries is the primary emphasis of the paper. Although there has already been significant research on biofuel and biofuel-related crops, much of the previous research has sought to find a relationship among commodity prices. Only a few published papers have been concerned with volatility spillovers. However, it must be emphasized that there have been numerous technical errors in the theoretical and empirical research, which needs to be corrected. The paper not only considers futures prices as a widely-used hedging instrument, but also takes an interesting new hedging instrument, ETF, into account. ETF is regarded as index futures when investors manage their portfolios, so it is possible to calculate an optimal dynamic hedging ratio. This is a very useful and interesting application for the estimation and testing of volatility spillovers. In the empirical analysis, multivariate conditional volatility diagonal BEKK models are estimated for comparing patterns of covolatility spillovers. The paper provides a new way of analyzing and describing the patterns of covolatility spillovers, which should be useful for the future empirical analysis of estimating and testing covolatility spillover effects.

Keywords: Energy and agriculture, covolatility spillovers, spot prices, futures prices, exchange traded funds, biofuels, optimal dynamic hedging.

JEL: C32, C58, G13, Q14, Q42.

1. Introduction

With the continuous growth in the global population and rapid economic development, there are some problems that will become crucial in the future, such as food supplies and energy shortage. Both food and energy shortage are associated with energy and agricultural commodities and markets. Consequently, expansions of energy and agricultural markets are still possible, and necessary, even though these industries are already heavily traded.

In addition, the agricultural and energy industries are closely related, both biologically and financially. The paper discusses the relationship and the interactions on price and volatility, with special focus on the volatility spillover effects for these two industries.

In the academic literature, researchers have examined the alternative channels in which these two industries can impact on each other. For instance, the increasing use of green energy or biofuel might cause a trade-off, which suggests that agricultural commodity producers use arable land to grow agricultural commodities for biofuel instead of food consumption. Moreover, fertilizers are also made by the use of energy commodities, such as crude oil.

Ajanovic (2011) is concerned about the trade-off, and suggests that, although there is not a significant impact of biofuel on crop prices, the issue should still be of concern as the growth of bioenergy in the past was just moderate. Even if all crops and forests were used, it would still not be possible to substitute all the fossil fuel used today. Rathmann et al. (2010) studied the land use competition for producing food and biofuel. Patterns of land use have changed, driven by biofuel, and this has questioned how biofuel can be produced in a sustainable manner without unduly competing with the increasing demand for food.

In the USA, 15.7% of total energy consumption is used to produce food, and 10% of crude oil is used to make fertilizer, among other related products. Therefore, the interaction and volatility spillovers (namely, the delayed effect of a returns shock in one asset on the subsequent volatility or covolatility in another asset) between the energy and agricultural industries is the primary emphasis of the paper. Although there has already been significant research on biofuel and biofuel-related crops, much of the previous research has sought to find a relationship among commodity prices. Only a few papers have been concerned with volatility spillovers. However, it must be emphasized that there have been numerous technical errors in the theoretical and empirical research, which needs to be corrected.

Multivariate conditional volatility models, such as BEKK and DCC, are widely used to model and test volatility spillovers. In the paper, the diagonal and scalar BEKK models will be used, but not the DCC model. The optimal dynamic hedging ratio can be calculated by using the estimated volatility spillovers, or interdependences. The optimal hedging ratio can be derived to a form in which the covariance between the hedged asset, or commodity, and the hedging instrument is the numerator, and the variance of the hedging instrument is the denominator. The empirical results presented in the paper should give significant insights to financial and commodity investors. For example, investors in agricultural commodities should not only be careful about weather, disaster, and food reserves, but also about variations in the energy market.

As the agricultural and energy markets have many channels through which to affect each other, the paper will focus primarily on green energy and agricultural commodities, specifically, biofuel and biofuel-related agricultural commodities, where the biological and financial impacts are more clear, direct and obvious.

Biofuel is a fuel produced through biological processes, such as agriculture and anaerobic digestion, rather than a fuel produced by geological processes, such as fossil fuels. It can be produced by corn, rapeseed, sugarcane, cassava, barley or other agricultural products. Unlike fossil fuels, biofuel is renewable and sustainable, which means it can largely be produced in a short period of time.

Agricultural commodities and biofuel are closely related in a number of different ways. Physically, they are connected by farmland, technology, or processes of producing, such as the trade-off through limited farmland, or the possibility of producing biofuel through different agricultural sources, specifically, corn, sugarcane and algae.

Financially, high crude oil prices lead to high food prices, as biofuel will be a cheaper substitute when the oil price is high. A high crude oil price will increase the demand for green energy, such as biofuel, and the growth in demand for biofuel will subsequently increase the demand for agricultural commodities. Du and Hayes (2009) suggest that the increase in bio-ethanol lowers gasoline prices as ethanol is a substitute for gasoline.

Furthermore, government policy also plays an important role in the connection between biofuel and agricultural commodities. The USA relies on bio-ethanol as a substitute for fossil fuels. However, corn as a source of biofuel is not generally an efficient source as compared with sugarcane, although it is cost-efficient for the USA (see Figure 1). The widespread use of bio-ethanol in Brazil is not for environmental issues but owing to increasing the independence of energy supplies after the Oil Crisis in 1973. Such policies can have great impacts on the energy and agricultural markets. McPhail and Babcock (2011) examine the influence of biofuel policies on biofuel and gasoline prices, and suggest that government policies have impacts on commodity prices in the biomass and biomass-related markets.

Biofuel comprises two major types, namely, bio-ethanol and bio-diesel (see Figure 2). The paper will focus on bio-ethanol, but not bio-diesel, primarily for health and pollution considerations. After numerous scandals, such as Volkswagen faking its own toxic vapor emission test results, it is clear that most diesel automobiles will not be able to meet the exacting US regulations. The diesel car market is facing a devastating situation, which is definitely having a significant negative impact on the demand for diesel.

Moreover, diesel emission contains carcinogens (that is, cancer-causing substances), which may lead to various cancers in other chronic physical ailments. Moreover, diesel creates far greater pollution than does gasoline. The costs of health and medical care for cancer and other illnesses from pollution will become unthinkable. In the long run, diesel is unsustainable, as is bio-diesel.

Bio-ethanol is usually used as a gasoline additive to increase octane and improve vehicle emissions. According to the proportion of the ethanol in the mixture, there are products like E5 (that is, 5% is ethanol), E10, and so on. USA and Brazil use bio-ethanol widely as bio-ethanol is a substitute for fossil fuels.

Indeed, not everyone is willing to support bio-ethanol, and its pros and cons are also debateable. However, bio-ethanol may be the best and easiest option until there is a broad-based solution for alternative energy sources. The expansion of the bio-ethanol market is still possible, especially as bio-ethanol has recently reached an 18-month high, so that there is an expectation of rising production. Moreover, the recently reported news that the Environmental Protection Agency (EPA) plans to boost further ethanol use in gasoline gives significant encouragement to biofuel producers (see Figure 3).

For agricultural products, attention will be on the commodities which can be converted into biofuel, especially bio-ethanol. Moreover, the financial derivatives of these commodities will also be taken into the consideration, such as futures prices. Another derivative, namely, exchange-traded funds (ETF), will also be considered in the paper for a more comprehensive analysis of these industries, and will provide further analysis for hedging purposes. This is the one of the primary purposes and applications for testing covolatility spillovers.

In recent years, investors have been targeting increasingly specific niches, so there have been numerous financial indices, which have a wide range from the whole market to a sub-market sector, or even only a basket of several assets in the market. These spot indices provide investors with the information to understand their targets. However, spot prices or spot indices are not tradeable. As one of the solutions for this inherent need, an Exchange Traded Fund (ETF) is an investment fund that tracks an index and replicates its performance, and indirectly makes the stock index tradeable by trading the ETF. Over the past few years, there has been a flourishing expansion of ETF in financial markets.

As ETF is designed to provide investors with access to the returns of various market benchmarks, there are several reasons why investors it appealing. First, as a derivative that is underlying an index, which is usually a weighted mean of different assets, ETF is already diversifying risks. Second, for investors who are not willing to spend time in analyzing individual stocks but are optimistic about the whole market, ETF is a simple and time-saving solution. In addition, ETF also provides accessibility to some assets, such as precious metal index, energy index, or even some stocks at a high price, which are not easy to trade or acquire for small individuals with only limited resources.

The advantages of ETF are not merely those stated above, but also some more practical functions, such as offering both tax efficiency and lower transaction costs. Poterba and Shoven (2002) compared the pre-tax and post-tax returns of ETF and traditional mutual funds, and suggest that ETFs offer taxable investors a method of holding broad baskets of stocks that are comparable to those of low-cost index funds.

Furthermore, as the ETF replicates the performance of an index, its contents and holdings of assets is highly transparent. Therefore, investors can understand the features of the portfolio and take appropriate action. Although the ETF is referred to as a fund, it is actually traded like a stock, which is easy to buy and sell, and usually with high liquidity. Therefore, with the capability of taking long and short positions, ETF is definitely an alternative option as a hedging instrument.

ETF is gradually regarded as a hedging instrument by more and more investors. However, its importance seems to have been both underrated and understated, and there does not seem to have been as great an emphasis on hedging with ETF as is importance might dictate. As both prices underlie a basket of assets, and are also designed to trade the spot index, ETF has a similar concept to that of index futures. Therefore, some investors treat ETF in the same manner as index futures when they manage their portfolios. The biggest difference between these two financial derivatives is that ETF does not have a maturity date, or the period is much longer than a futures contract that can be regarded as having no maturity date.

In the past, corporations could only use futures as a hedging instrument for the long term. However, they had to roll over or switch positions every month, and it brings about transaction costs, spread costs, and other related issues. With ETF, corporations can save a lot of effort by eliminating their switching positions every month as there is no maturity date for ETF. The emergence of ETF, as an alternative option for hedging, provides investors alternative choices and strategies for hedging.

In short, the main purpose of the paper is to use a multivariate conditional volatility model to estimate and test volatility spillovers between energy and agricultural commodities and markets. Further applications of the estimated volatility spillovers on hedging strategies will be discussed. The result will be used to provide some hedging advice between the energy and agricultural industries, especially between bio-ethanol and bio-ethanol-related agricultural commodities.

2. Literature Review

Numerous papers have studied the interactions of commodities in agricultural and agriculture-related markets, such as the transmission or spillover effects of prices and risk. Chang et al. (2012) used the M-TAR (Momentum-Threshold) model and VECM (Vector Error Correction Model) to analyze the price transmission effects for bio-energy and energy crops, namely, corn, soybeans and sugar. Bio-ethanol were found to be useful as a hedging instrument against prices in agricultural and food markets. Serra and Zilberman (2013) review the literature on the price transmission in the biofuel and agricultural industries. They conclude that energy prices drive long-run agricultural price levels, and the instability in energy markets is subsequently transferred to food markets.

For spillover effects on the volatility or risk between different assets, which is the primary issue in the paper, multivariate conditional volatility models are needed, which can be divided into two types. The first approach uses conditional covariances, such as the Vech and BEKK models of Engle and Kroner (1995), while the second approach uses conditional correlations, such as the CCC model of Bollerslev (1990) and DCC model of Engle (2002). Trujillo-Barrera et al.

(2012) use the Full BEKK model to analyze and measure the risk or volatility spillovers for US crude oil, bio-ethanol and corn futures. The empirical results indicate that corn has a significant volatility spillover effect on bio-ethanol.

Du and McPhail (2012) explain the corn-ethanol relation, specifically, ethanol shocks have the largest impact on corn prices, and vice-versa, by using the scalar DCC model to test volatility spillovers in the corn and bio-ethanol industries. However, Chang et al. (2015) give a critical review and appraisal of the extant literature, and suggest that the literature is incorrect in the use of the Full BEKK and DCC models to test for volatility spillover effects.

The next part of the paper on model specifications will follow closely the presentation in Chang et al. (2015), in which they discuss previous research that has tested for volatility spillovers between the bio-ethanol and agricultural markets. These so-called tests have been based on estimating alternative multivariate conditional volatility models, specifically variations of the BEKK and DCC models. Chang et al. (2015) develop three novel definitions of volatility and covolatility spillovers, which will be used in the paper. The empirical applications of different models are evaluated in terms of the new definitions and appropriate statistical criteria.

With the curse of dimensionality and without regularity conditions, the full BEKK model has serious technical deficiencies and limitations, so valid statistical tests of volatility spillovers are not possible. In contrast, the regularity conditions of the diagonal BEKK can be verified, and valid statistical tests of volatility spillovers can be established. The DCC model, which has no regularity conditions or asymptotic properties, cannot test for volatility spillovers statistically by using the associated conditional covariances as it has no regularity conditions or statistical properties.

For their theoretical and practical appraisal, Chang et al. (2015) choose 11 published empirical papers that have used the multivariate BEKK model, and two papers that estimated both the full BEKK and scalar DCC models. Of these empirical papers, only Algieri (2014) used the diagonal BEKK model, and much of the published research used the full BEKK model. Based on the theoretical result that the full BEKK model is not valid for testing volatility spillovers, there has not been much research on volatility spillovers that has used the appropriate model and techniques. Therefore, the paper will use the diagonal or scalar BEKK models, but not the full BEKK or scalar DCC models.

This paper will also refer to the earlier research on volatility spillovers using conditional correlations, such as Manera et al. (2006) and Chang et al. (2009). Both papers are concerned with modelling conditional correlations, and Chang et al. (2010) is concerned with forecasting volatility spillovers. Given the recent novel definitions of covolatility spillovers and the discussion in Chang et al. (2015), the literature is not strictly correct. However, the published papers provide a train of thought and concepts about modelling and estimating volatility spillovers that might prove useful in comparative empirical analysis.

Chang, McAleer and Wang (2016) analyze the empirical results by using the new definitions of volatility spillovers and appropriate models, namely diagonal BEKK. They calculate covolatility spillover effects for spot and futures prices in the bio-ethanol, sugarcane and corn markets. The results indicate that bio-ethanol and agricultural commodities should be considered together in financial portfolios for hedging purposes. The paper will basically follow their method, and provide further empirical research and discussion.

Chang, Hsieh and McAleer (2016) also analyze the linkages between VIX and ETF returns. They applied the VAR and diagonal BEKK models using ETF data. Their analysis provides the paper with the idea of adding ETF in the empirical analysis as ETF is a specific market indicator, as well as a potentially interesting hedging instrument.

Regarding the analysis of spillover effects of ETF, Chen and Huang (2010) suggest that, not only does ETF have a better performance than does the stock index in developed countries, but the volatility spillover effects also have bilateral influences. It has also been shown in Chang, McAleer and Wang (2016) that the various commodities in the bio-ethanol and related markets have bilateral covolatility spillovers.

Following the idea of hedging using the multivariate GARCH model in Chang et al. (2011), the paper will also discuss the application of estimated spillovers for hedging purposes. In particular, we will use the results given in Chang et al. (2015), and focus on optimal hedging between the biofuel and agricultural industries.

3. Model Specifications

The primary purpose of the paper is to test for spillover effects among several assets, namely spot, futures, financial index and ETF, in the agricultural and energy markets. Testing of spillovers requires estimation of multivariate conditional volatility models with appropriate regularity conditions and asymptotic properties of the Quasi Maximum Likelihood Estimators (QMLE) of the associated parameters underlying the conditional means and conditional variances (for further details, see, for example, McAleer (2005), McAleer et al. (2008)).

As the first step in the estimation of multivariate conditional volatility models is the estimation of multiple univariate volatility models, this section is organized as follow:

(1) A brief discussion of the most widely-used univariate conditional volatility model;

(2) A discussion of the most widely-used multivariate models of conditional volatility;

(3) A definition of three novel spillovers effects.

The first step in estimating multivariate models is to estimate and retain the standardized shocks from the conditional mean returns shocks, which are based on univariate models. The most widely used univariate conditional volatility model, namely GARCH, will be presented briefly, followed by the one of the most widely used multivariate conditional covariance models, namely variations of BEKK.

Some of the following material can be found in, for example, McAleer (2005), McAleer at el. (2008), and Chang et al. (2015). Consider the conditional mean of financial returns, as follows:

$$y_t = E(y_t|I_{t-1}) + \varepsilon_t \tag{1}$$

where the return, $y_t = \Delta \log P_t$, represents the log-difference in financial commodity or agricultural prices (P_t), I_{t-1} is the information set at time *t-1*, and ε_t is conditionally heteroskedastic. In order to derive conditional volatility specifications, it is necessary to specify the stochastic processes underlying the returns shocks, ε_t.

3.1 Univariate Conditional Volatility Models

Alternative univariate conditional volatility models are of interest in single index models to describe individual financial assets and markets. Univariate conditional volatilities can also be used to standardize the conditional covariances in alternative multivariate conditional volatility models to estimate conditional correlations, which are particularly useful in developing dynamic hedging strategies.

The three most popular univariate conditional volatility models are GARCH, GJR, and EGARCH. However, only GARCH is presented below as the focus of the paper is on estimating and testing spillover effects using multivariate conditional volatility models.

3.1.1 Random Coefficient Autoregressive Process and GARCH

Consider the random coefficient autoregressive process of order one:

$$\varepsilon_t = \phi_t \varepsilon_{t-1} + \eta_t \qquad (2)$$

where

$\phi_t \sim iid(0, \alpha)$,

$\eta_t \sim iid(0, \omega)$,

and $\eta_t = \varepsilon_t / \sqrt{h_t}$ is the standardized residual.

Tsay (1987) derived the ARCH(1) model of Engle (1982) from equation (1) as:

$$h_t = E(\varepsilon_t^2 | I_{t-1}) = \omega + \alpha \varepsilon_{t-1}^2 \qquad (3)$$

where h_t is conditional volatility, and I_{t-1} is the information set available at time t-1. The use of an infinite lag length for the random coefficient autoregressive process in equation (2), with appropriate geometric restrictions (or stability conditions) on the random coefficients, leads to the GARCH model of Bollerslev (1986). From the specification of equation (2), it is clear that both ω and α should be positive as they are the unconditional variances of two different stochastic processes.

In order to accommodate volatility spillover effects, alternative multivariate volatility models of the conditional covariances are available. Examples include the diagonal model of Bollerslev et al. (1988), the Vech and diagonal Vech models of Engle and Kroner (1995), the Baba, Engle, Kraft, and Kroner (BEKK) multivariate GARCH model of Baba et al. (1985) and Engle and Kroner (1995), the constant conditional correlation (CCC) (specifically, multiple univariate rather than multivariate) GARCH model of Bollerslev (1990), the Ling and McAleer (2003) vector ARMA- GARCH (VARMA-GARCH) model, the VARMA–asymmetric GARCH (VARMA- AGARCH) model of McAleer et al. (2009), the Engle (2002) dynamic conditional correlation (technically, dynamic conditional covariance rather than correlation model) (DCC), and the Tse and Tsui (2002) varying conditional correlation (VCC) model.

The two most widely-used multivariate conditional volatility models are BEKK and DCC. However, only BEKK is presented below as it is the most widely-used multivariate conditional volatility model, with appropriate regularity conditions and asymptotic properties under appropriate parametric restrictions. The DCC model has no known regularity conditions, and hence no asymptotic properties, so that no valid statistical inference is possible. For further details on and properties of these multivariate models see, for example, McAleer (2005) and Hafner and McAleer (2014).

3.2 Multivariate Conditional Volatility Models

Multivariate conditional volatility GARCH models are often used to analyze the interaction between the second moments of returns shocks to a portfolio of assets, and can model and the possible risk transmission or spillovers among different assets. The multivariate extension of univariate GARCH in equation (3) is given as variation of the BEKK model in Baba et al. (1985) and Engle and Kroner (1995).

In order to establish volatility spillovers in a multivariate framework, it is useful to define the multivariate extension of the relationship between the returns shocks and the standardized residuals, that is, $\eta_t = \varepsilon_t / \sqrt{h_t}$. The multivariate extension of equation (1), namely $y_t = E(y_t | I_{t-1}) + \varepsilon_t$, can remain unchanged by assuming that the three components are now $m \times 1$ vectors, where m is the number of financial assets. The multivariate definition of the relationship between ε_t and η_t is given as:

$$\varepsilon_t = D_t^{1/2} \eta_t \qquad (4)$$

where $D_t = diag(h_{1t}, h_{2t}, \dots, h_{mt})$ is a diagonal matrix comprising the univariate conditional volatilities. Define the conditional covariance matrix of ε_t as Q_t. As the $m \times 1$ vector, η_t, is assumed to be *iid* for all m elements, the conditional correlation matrix of ε_t, which is equivalent to the conditional correlation matrix of η_t, is given by Γ_t. Therefore, the conditional expectation of the process in equation (4) is defined as:

$$Q_t = D_t^{1/2} \Gamma_t D_t^{1/2} \qquad (5)$$

Equivalently, the conditional correlation matrix, Γ_t can be defined as:

$$\Gamma_t = D_t^{-1/2} Q_t D_t^{-1/2} \qquad (6)$$

Equation (5) is useful if a model of Γ_t is available for purposes of estimating Q_t, whereas (6) is useful if a model of Q_t is available for purposes of estimating Γ_t.

The vector random coefficient autoregressive process of order one is the multivariate extension of equation (2), and is given as:

$$\varepsilon_t = \Phi_t \varepsilon_{t-1} + \eta_t \tag{7}$$

where

ε_t and η_t are $m \times 1$ vectors, and Φ_t is an $m \times m$ matrix of random coefficients, and

$\Phi_t \sim iid(0, A)$,
$\eta_t \sim iid(0, QQ')$.

Technically, a vectorization of a full (that is, non-diagonal or non-scalar) matrix *A* to *vec A* can have dimension as high as $m^2 \times m^2$, whereas vectorization of a symmetric matrix *A* to *vech A* can have dimension as low as $m(m-1)/2 \times m(m-1)/2$.

The matrix *A* is crucial in the interpretation of symmetric and asymmetric weights attached to the return shocks, as well as a subsequent analysis of spillover effects.

3.2.1 Triangular, Hadamard and Full BEKK

Without actually deriving the model from an appropriate or known stochastic process, Baba et al. (1985) and Engle and Kroner (1995) considered the full BEKK model, as well as the special cases of triangular and Hadamard (element-by-element multiplication) BEKK. The specification of the multivariate model is given below:

$$Q_t = QQ' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BQ_{t-1}B' \tag{8}$$

where A and B in equation (8) can be the full, Hadamard or triangular matrices, under appropriate parametric restrictions.

Although it is possible to examine spillover effects using each of these three models, it is not possible to test for or analyze the spillover effects as the QMLE for the model in equation (8) have no known asymptotic properties. However, estimation of the full, Hadamard and triangular BEKK models is available in some standard econometric and statistical software packages, though it is not clear how the likelihood functions might be determined. Moreover, the so-called "curse of dimensionality", whereby the number of parameters to be estimated is excessively large, that is, $m(5m+1)/2$, makes convergence of any estimation algorithm somewhat problematic.

This is in sharp contrast to a number of published papers in the literature, whereby volatility spillovers have been tested incorrectly based on the off-diagonal terms in the matrix A in equation (8) (for further details, see Chang et al. (2015)).

3.2.2 Diagonal and Scalar BEKK

As a special case of full BEKK, where A is either a diagonal matrix or the special case of a scalar matrix, $A = aI_m$, McAleer et al. (2008) showed that the multivariate extension of GARCH(1,1) from equation (7), incorporating an infinite geometric lag in terms of the returns shocks, is given as the diagonal or scalar BEKK model, and the specification of the multivariate model is the same as the specification in equation (8), namely:

$$Q_t = QQ' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BQ_{t-1}B' \tag{9}$$

except that A and B are both either diagonal or scalar matrices, rather than full, Hadamard or triangular matrices, as in (8).

McAleer et al. (2008) showed that the QMLE of the parameters of the diagonal or scalar BEKK models were consistent and asymptotically normal, so that standard statistical inference on testing hypotheses is valid. Moreover, as Q_t in (9) can be estimated consistently, Γ_t in equation (6) can also be estimated consistently.

Further discussion of applying the diagonal BEKK model on testing volatility spillover effects will be presented in Section 3.3, together with three novel definitions of volatility spillovers. Another widely-used multivariate conditional volatility model, DCC, will not be presented or used in the paper as it has no regularity conditions and asymptotic properties (for further details, see Aielli (2013), Caporin and McAleer (2013), and Hafner and McAleer (2014)).

3.3 Full and Partial Volatility and Covolatility Spillovers

Testing for spillovers in the literature is typically both confused and confusing. Indeed, many so-called tests of spillovers are not, in fact, tests of spillovers. The following section presents three novel tests for spillovers, namely, full volatility spillovers, full covolatility spillovers, and partial covolatility spillovers.

Volatility spillovers are defined as the delayed effect of a returns shock in one asset on Q_t, the subsequent volatility or covolatility in another asset. Therefore, a model relating to returns shocks is essential, and this will be addressed in the following sub-section. Spillovers can be defined in terms of full volatility spillovers and full covolatility spillovers, as well as partial covolatility spillovers, as follows, for $i,j,k = 1,\ldots, m$:

1) Full volatility spillovers: $\partial Q_{iit}/\partial \varepsilon_{kt-1}$, $k \neq i$

2) Full covolatility spillovers: $\partial Q_{ijt}/\partial \varepsilon_{kt-1}$, $i \neq j,\ k \neq i, j$

3) Partial covolatility spillovers: $\partial Q_{ijt}/\partial \varepsilon_{it-1}$, $i \neq j$

Full volatility spillovers occur when the return shock from financial asset k affects the volatility of a different financial asset i.

Full covolatility spillovers occur when the return shock from financial asset k affects the covolatility between two different financial assets, i and j.

Partial covolatility spillovers occur when the return shock from financial asset i affects the covolatility between two financial assets, i and j.

When $m = 2$, only 1) and 3) are possible as full covolatility spillovers depend on the existence of a third financial asset.

As mentioned above, spillovers require a model that relates the conditional volatility matrix, Q_t, to a matrix of delayed returns shocks. The two most frequently used models of multivariate conditional covariances are the BEKK and DCC models, with appropriate parametric restrictions, which were discussed in the previous section. This paper follows the recommendation from Chang et al. (2015) that only the scalar and diagonal BEKK models be used for empirical analysis.

In terms of volatility spillovers using diagonal BEKK, as the off-diagonal terms in the second term on the right-hand side of equation (9), $A\varepsilon_{t-1}\varepsilon'_{t-1}A'$, have typical *(i,j)* elements $a_{ii}a_{jj}\varepsilon_{it-1}\varepsilon_{jt-1}, i \neq j,\ i,j = 1, \dots, m$, there are no full volatility or full covolatility spillovers. However, partial covolatility spillovers are not only possible, but they can also be tested using valid statistical procedures.

For full volatility and covolatility spillovers, full BEKK is needed. However, the curse of dimension for full BEKK makes the process problematic, not to mention the lack of regularity conditions and asymptotic properties of the QMLE of the parameters. In short, while full BEKK may seem like the holy grail of multivariate GARCH models, this essentially relies on wishful thinking and is devoid of a statistical framework.

Therefore, in the empirical analysis, the diagonal BEKK model will be used to test for partial covolatility effects. The diagonal BEKK model is given as equation (9), where the matrices *A* and *B* are given as:

$$A = \begin{bmatrix} a_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & a_{mm} \end{bmatrix}, B = A = \begin{bmatrix} b_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & b_{mm} \end{bmatrix}$$

Partial covolatility spillovers are defined as the effect of a shock in commodity *i* at time *t-1* on the subsequent covolatility between *i* and another commodity at time *t*, which can be presented as:

$$\frac{\partial Q_{ijt}}{\partial \varepsilon_{it-1}} = a_{ii} \times a_{jj} \times \varepsilon_{jt-1}, \qquad i \neq j$$

where a_{ii} and a_{jj} are the elements in *A* of diagonal BEKK, and ε_{jt-1} is the return shock of *j* at time *t-1*.

If $a_{ii}, a_{jj} > 0$, there is a non-zero spillover effect from the return shock of asset *i* at *t-1* to the covolatility between assets *i* and *j*. It is worth mentioning that the return shock of asset *i* at time *t-1* , ε_{it-1}, does not affect the spillover effect of asset *i* at *t-1* on the covolatility between assets *i* and *j* at time *t*.

Furthermore, spillover effects vary for each observation at *t-1*. However, it seems unnecessary to calculate every spillover for every *t-1* to highlight the spillover effects, in general. Therefore, the paper will use the mean return shocks to calculate the mean covolatility spillover effects in order to provide a general discussion for the energy and agricultural markets.

4. Data and Variables

The paper is concerned with the relationships, interactions, and spillovers effects between the agricultural and energy markets, particularly bio-ethanol and ethanol-related agricultural commodities, such as corn and sugar.

Four different prices are used in the paper, namely spot price, futures price, ETF price, and the prices of the index tracked by ETF. Therefore, four prices for each of the three commodities from the agricultural and bio-ethanol markets, namely, twelve variables are considered. All the variables use daily time series data for the empirical analysis. For each series, the sample period is from 25 June 2010 to 6 May 2016, for a total of 1531 observations for prices, and 1530 observations for returns. Being a relatively new financial product, the availability of data on ETF limits the length of the sample period.

The data on agricultural commodities, both corn and sugar, are downloaded from Datastream, and are originally sourced from United Stated Department of Agriculture (USDA). Corn spot is Corn Number 2 Yellow (cents/bushel), and the ticker symbol is CORNUS2. Sugar spot is Raw Sugar - International Sugar Agreement (ISA) (cents/pound), and the ticker symbol is WSUGDLY. There are several kinds of spot prices for ethanol that are provided by both Datastream and Bloomberg. However, the data typically change only once or twice each week, despite the fact that ethanol spot prices are presented as daily data.

Therefore, a free on board (FOB) spot price, Bloomberg Ethanol Prompt mth fob spot price/Chicago (cents/gallon), is used for ethanol. Compared with the original ethanol spot price series, the FOB ethanol spot price has greater movement and higher correlations with ethanol futures. The FOB price of ethanol is regarded as the ethanol spot price in the paper, and its ticker symbol is ETHNCHIC index, as sourced from Bloomberg.

Corn futures, Corn Continuous (ticker symbol: CC.CS00), is traded on the electronic trading platform of the Chicago Board of Trade (CBOT), and is expressed in US cents per bushel. Sugar futures, Sugar # 11 (ticker symbol: NSBCS00), is expressed in US cents per pound, and is traded at the Coffee, Sugar & Cocoa Exchange (CSCE). Ethanol futures, Ethanol Continuous (ticker symbol: CZEC00), is traded on eCBOT, and is expressed in US dollars per gallon. All the data on futures are obtained from Datastream.

As the ETF tracks an index, commodity, or a basket of assets, starting from the introduction of the index will be more convenient. However, the existence of ETF is the reason these indices are chosen, as we are interested in the volatility spillovers and hedging discussion of ETFs. The three indices and their ticker symbols are Teucrium Corn Fund Benchmark Index (TCORN Index), Bloomberg Sugar Subindex Total Return (BCOMSBTR Index), and BofA Merrill Lynch Commodity index eXtra Biofuels Total Return Index (MLCXBXTR Index).

The corn index, TCORN, represents a fund that invests in corn futures traded on CBOT, and is designed to reflect the daily changes in the percentage of a weighted average for three corn futures, namely, the second-to-expire contract, third-to-expire contract, and the contract expiring in December following the expiration of the third-to-expire contract. These three futures contracts are all weighted about 30-35 percent, so the TCORN index will not roll all of its holdings every month, potentially reducing the impact of contango on price.

The sugar index was formerly known as the Dow Jones – UBS Sugar Subindex, which is composed of futures contracts on sugar. It reflects the return of the underlying commodity futures price movements.

As the bio-ethanol market is a young and relative small market, bio-ethanol and bio-diesel are widely regarded as a single “bio-mass” or “bio-fuel” market. The MLCXBXTR index is a benchmark for the bio-energy sector, and contains seven types of commodities, namely, sugar, corn, barley, soy bean, soy bean oil, canola and rapeseed. The index is heavily weighted by soybeans (32.7%), corn (21.1%), soybean oil (19.5%), and sugar (15.7%), while the proportions of the sources of bio-ethanol, namely corn and sugar, are around 36%. The index is considered in the paper, as the focus is on spillover effects, that is, on the interactions between assets, and not the value of ethanol. Therefore, with a large proportion of ethanol, this index is taken to represent the bio-ethanol market for purposes of the empirical analysis.

For the paper, there are limited choices of data on ETFs in these industries, especially biofuel ETF, as it is a relatively young product of a young market. Corn ETF is the Teucrium Corn Fund (ticker symbol: CORN US equity), which tracks the performance of Teucrium Corn Fund Benchmark Index. Sugar ETF is the iPath Bloomberg Sugar Subindex Total Return ETN (SGG US equity), which replicates the performance of the Bloomberg Sugar Subindex Total Return.

For bio-ethanol, as there is not a separate bio-ethanol ETF, biofuel ETF is taken into account. Biofuel ETF is the ELEMENTS Linked to the MLCX Biofuels Index (Exchange Series) - Total Return ETN (FUE US equity), which tracks the performance of the MLCX Biofuel Index, but lacks data. However, the index ELEMENTS Linked to the MLCX Biofuels Index Total Return IOPV, gives the calculated implied value of biofuel ETF, which will be used in the paper. All the data on the three ETFs are downloaded from Bloomberg, where ETF is listed under the category of equity in Bloomberg, Therefore, the ticker symbol will contain “equity”.

Without the ethanol ETF, recent news articles have suggested that interest in the continuing ethanol boom should pay attention to corn and biofuel ETFs. As a large proportion of corn produced in the USA is converted to ethanol, corn ETF is definitely an alternative option of analyzing bio-ethanol, as does biofuel ETF, which contains a high proportion of ethanol-related crops. Therefore, these two ETFs not only have a close relationship with the bio-ethanol market, but might also be suitable for estimating spillovers effects. Consequently, corn ETF and biofuel ETF are considered in the estimation and testing of spillover effects.

The endogenous variables used in the empirical analysis are the daily return rates, where the rate of return is obtained as the natural logarithm first difference in two consecutive daily price data, multiplied by 100. $Corn_s$, $Sugar_s$, and $Ethanol_s$ represents the returns on spot prices of corn, sugar, and bio-ethanol, respectively. $Corn_f$, $Sugar_f$, and $Ethanol_f$ represents the returns on futures prices of corn, sugar, and bio-ethanol, respectively. Furthermore, for $Corn_i$, $Sugar_i$, $Ethanol_i$, $Corn_e$, $Sugar_e$, $Ethanol_e$, the subscripts "i" and "e" denote returns on the index and ETF, respectively.

As mentioned previously, the ethanol index and ETF do not comprise only ethanol, but are actually a biofuel index which contains a high proportion of bio-ethanol and ETF, which tracks the performance of the biofuel index. Although they are not precise, $Ethanol_i$ and $Ethanol_e$ are used to denote these two variables in the following discussion for convenience. The variables are defined in Table 1.

[Insert Table 1 here]

The descriptive statistics for these variables are shown in Table 2. The means are rather small, and most are negative, especially for the sugar industry. However, the corn industry is mainly positive. It is possible that poor weather conditions and the continually increasing demand for corn in the past few years are the primary reasons. Recently, stockpiles have been increasing, and corn prices are still rising, according to recent reports in the Wall Street Journal. The relatively low crude oil prices in the previous year might have affected the price of ethanol, so the spot and futures returns are negative. For the biofuel index and ETF, it might have been the effect of bio-diesel, which is not a direct substitute for gasoline.

The highest standard deviations for both the spot and futures market are for ethanol, while the highest standard deviations for the financial index and ETF are for sugar. The returns have different degrees of skewness, with most of the returns being negatively skewed, which means more extreme losses occurred than extreme gains. All of the returns have kurtosis that is higher than 3, indicating that they have higher probabilities of extreme market movements. The Jarque-Bera test suggests that none of the data series exhibits a normal distribution.

[Insert Table 2 here]

As shown in Figure 5, the volatility of the returns of spot, futures, financial index and ETF in the corn, sugar and bio-ethanol markets display the phenomenon of volatility clustering. The unit root tests for all variables are also given in Table 3, which show that all the returns series are stationary.

[Insert Table 3 and Figure 4 here]

The correlations of both returns and prices are given in Tables 4 and 5. In the same industry, the correlations of prices are higher, which is not surprising. This holds widely, except for the ethanol market, which makes sense as the financial index and ETF are means of bio-diesel and bio-ethanol. Across the industries, the correlations of prices between the corn and ethanol markets are all higher than the correlations between the sugar and ethanol markets, especially for the financial index and ETF. This result would seem to confirm recommendations from the news media that investors who are interested in the continuing ethanol boom should pay attention to the corn ETF in the absence of ethanol ETF.

Moreover, the correlations of returns basically follow the same pattern of correlations as prices, but there is no distinct correlation that is particularly high or low. The correlations between the financial index and ETF are a lot higher than others for each industry as the ETF virtually replicates the performance of the financial index.

[Insert Tables 4 and 5 here]

5. Empirical Results

5.1 Testing Partial Covolatility Spillovers

Much of the previous and questionable research in the testing of volatility spillovers has been concerned with testing the significance of the estimates of the weighting matrix *A* in the BEKK model. The off-diagonal terms in the matrix *A* in the Full BEKK model have widely been regarded as capturing spillover effects. Indeed, the matrix *A* seems to be an indispensable concept in the literature. However, the matrix *A* only represents the weights or multipliers, and do not actually capture the spillover effects.

The existing literature has missed a crucial issue, namely, the strict definition of volatility spillovers, namely the "delayed effect of a returns shock in one asset on the subsequent volatility or covolatility in another asset" (see Chang et al. (2015)). The numerous published papers have not bothered to differentiate the conditional covariance matrix, $Q_{ij,t}$ with respect to the return shock, $\varepsilon_{k,t-1}$, so the effect of $\varepsilon_{k,t-1}$ on volatility has not been tested. What the published papers are actually testing is the multiplier for the return shock in calculating volatility spillovers. In short, the published empirical results are not directly concerned with the return shock, and hence are also not directly concerned with testing volatility and covolatility spillovers.

As mentioned in Section 3, it is possible to test partial covolatility spillover effects through testing the significance of the matrix *A* in the diagonal BEKK model, as the partial covolatility spillover effects are only affected by the matrix *A* after differentiating the covariance matrix with respect to the return shocks.

Following Chang, McAleer and Wang (2016), the empirical analysis uses the VAR(1) – multivariate diagonal BEKK model to test partial covolatility spillovers for the purpose of calculating optimal dynamic hedging ratios. Twelve variables in the bio-ethanol and agricultural industries are used, including the new ETFs and the financial indices that are tracked by ETFs. The empirical analysis of Chang, McAleer and Wang (2016) is separated by different type of assets, such as the volatility spillovers of the corn spot price on ethanol spot price. Therefore, we are interested in testing the spillover effects between different types of agricultural and energy commodities, with an emphasis on optimal dynamic hedging of alternative spot prices using futures prices.

A 12 x 12 matrix that includes all the variables is estimated for the diagonal BEKK model, and the results are given in Table 6. The matrix *A* is a diagonal matrix which contains 12 diagonal terms, namely A*(i,i*), where *i* = 1, 2, …, 12. All the coefficients are statistical significant at the 1% level. For example, *A(1,1)* (or a_{11} in Section 3) is the weight or multiplier of the corn spot price return, *A(2,2)* is the weight or multiplier of the corn futures price return, and so on. The largest value of the weights is for ethanol futures, and the smallest is for ethanol ETF. Notwithstanding these estimates, they do not necessarily represent the magnitude of the volatility spillovers effects as they have not been multiplied by a return shock and by a weight of another agricultural or energy commodity.

For the corn market, all the multipliers are in the range 0.21 to 0.25, while the multipliers of the other two markets vary considerably. However, examination of the multipliers of the financial indices and ETFs shows that in all three markets they are fairly similar as ETF is a derivative that underlies the financial index, and hence replicates its performance. Consequently, the spot and futures prices might also be compared as futures prices are derivative of spot prices. For the corn and sugar markets, they are similar, but this does not hold for the ethanol market. The reason is probably because the data on the ethanol spot price is not as accurate as the corn and sugar spot prices, such as the lack of daily price movements, although they are daily prices. The correlation of ethanol prices and returns with futures prices are both lower than for the corresponding correlations of corn and sugar spot prices with their respective futures prices.

[Insert Table 6 here]

The mean return shocks are also estimated and reported in Table 6. Most of the mean estimated return shocks are positive, except for corn futures and ETF, and most of the ethanol industries. The larger return shock regardless of sign is corn ETF, while the smallest is the financial index of biofuel.

With the significance of all estimated elements in the Matrix A, the partial covolatility spillover effects can be calculated by using the general formula, $a_{ii} \times a_{jj} \times \varepsilon_{j,t-1}$. The a_{ii} of any assets times a_{jj} of a different asset, multiplied by the return shocks, means that any combination pairs of the twelve variables could be used to test partial covolatility spillover effects. If we are interested in a particular pair, for example, the spillover effect of the sugar index return on the corn index is 0.227946 $\times$ 0.227925 $\times$ 0.0079 = 0.00041132, and so on. The results of the calculated spillovers are not given, as there will be a total of 66 combinations (12 choose 2) and 132 partial covolatility spillovers. An alternative table, which is also a new way to interpret spillover effects, will be provided in the following discussion.

5.2 Comparison of the Patterns of Spillovers

With the overall picture for every pairs of spillover effects between any two assets, a new question arises, as follows: Will the spillover effects be the same when using only a 2 x 2 weight matrix in the diagonal BEKK model, as compared with every possible combination? In short, will the spillovers between two assets remain the same in other alternative combinations, such as 3 x 3 or 4 x 4 combinations of the diagonal BEKK model?

In order to check whether the covolatility spillovers of the same two assets, but in different combinations, will remain similar using casual empiricism, we estimated the extreme combinations, namely, the largest and the smallest matrices, 2 x 2 and 12 x 12, respectively. Consequently, for comparison, we calculated all the combinations pairs of the twelve variables.

Moreover, the large differences in the sizes of these two weight matrices *A* are likely to cause the actual numbers of spillover effects to be different. In addition, spillover effects vary for each observation at *t-1*, it is more important to compare the general patterns of the spillovers rather than the actual numbers of mean partial covolatility spillovers. Therefore, the patterns of every combination pair are summarized, and the interactions of the spillover effects of asset *i* on asset *j* and of asset *j* on *i*, are shown in Table 7.

[Insert Table 7 here]

For purposes of comparison, we use the following notation to describe the patterns of spillover effects. “Diagonal” and “scalar” describe the similarity of the multipliers, regardless of the return shocks. The terms are not a comparison of the spillovers effects as spillovers vary for each observation of return shocks at *t-1*, so it is possible that the spillovers of *i* on *j* may occasionally be larger or smaller. A comparison of the multiplier may be more reasonable than a comparison of the magnitude of the spillover effects. If the *A(i,i)* of two assets are similar, this will be referred to as a "scalar" effect. However, this should not be interpreted as having been estimated by the scalar BEKK, as it represents the elements of the weight matrix *A* estimated by the diagonal BEKK model. On the contrary, "diagonal" denotes that the elements of the weight matrix *A* are not similar, and the weights have also been estimated by the diagonal BEKK model.

Another important pattern is the sign of the mean spillover effects. Although the sign is either positive or negative, there can be different combinations, such as one weight being positive and another negative, or both being either positive or negative. "Symmetry" and "asymmetry" are used to describe these possible combinations. If one sign is positive and another is negative, either *i* positive and *j* negative, or the reverse, it is referred to as "asymmetry". On the other hand, "symmetry" indicates that the signs are either both negative or both positive for the spillover effects from *i* and *j*. The signs of the spillover effects are determined by the return shock in the previous period, so the spillover signs can vary considerably. A broad overall pattern between the assets can be shown by calculating the mean spillover effects.

Table 7 shows the patterns of the estimated partial covolatility spillover effects by using the VAR(1) – diagonal BEKK(1,1) model using twelve variables. When there is a return shock of asset *i* in the first column, the spillovers on *j* can be compared with the reverse spillovers of *j* on *i*. Most of the partial covolatility spillover pairs are diagonal and symmetric, represented as $\{D,S_{ym}\}$ in Table 7, which means their multipliers are different and the mean covolatility spillover effects have the same signs.

Only the spillovers between the corn and sugar indices, corn ETF and ethanol spot, sugar ETF and ethanol index are scalar, which means the multipliers are quite similar for the other pairs. The rest of the blocks represent the covolatility spillovers of pairs with asymmetric signs, which mean the spillovers between the two assets have opposite signs. Therefore, on average, the two spillovers of either *i* or *j* on the other have different directional effects. Moreover, the asymmetry of signs indicate that these two assets might be considered as a hedging portfolio as their spillover effects are moving in different directions.

Table 8 shows the patterns of the partial covolatility spillovers estimated using the 2 x 2 matrix, and are organized in the same way for purposes of comparison with the results of the 12 x 12 matrix. It appears that most of the patterns are also diagonal and symmetric as in the previous table, and very few have similar multipliers, but for different assets. The multipliers in the sugar index and sugar ETF is worth mentioning as the ETF is a derivative which replicates the financial index. In fact, the actual multipliers of ETF for corn and biofuel are also relatively similar compared with the wide gap of the other pairs.

Moreover, the blocks with asymmetry of signs is lesser and completely different from the previous table for 12 x 12, and all are concentrate on the ethanol spot with the other prices. This is because all the mean return shocks of ethanol spot with the other assets are the same as in the previous table, namely, negative, while most of the mean return shocks of the other assets are positive. Again, the situation might be caused by the data on ethanol spot prices, as noted previously. It is also possibly the reason why the partial covolatility spillovers of ethanol spot prices on the other two spot prices are not significant in the empirical results reported by Chang, McAleer and Wang (2016).

[Insert Table 8 here]

A comparison of Tables 7 and 8, namely, the two versions of patterns estimated by different sizes of the weight matrix *A*, specifically 12 x 12 and 2 x 2, respectively, is given in Table 9. Half of the patterns are exactly the same, whereby most are diagonal in the multipliers and symmetric in the signs. The rest are same in the patterns of either multipliers or signs, and only a few are completely different. The differences might be due to adding too many variables, which may also be highly correlated, and the interactions between these variables might lower the precision of the estimates.

Although there are some differences in the patterns of these two sets of results, both show that there are clear and definite volatility spillover effects for spot, futures, financial index and ETF in the energy and related agricultural markets.

[Insert Table 9 here]

6. Conclusion

The primary purposes of the paper were to test for volatility spillovers of spot prices, futures prices, financial index and ETF between bio-ethanol and related agricultural commodities, namely, corn and sugar, using the multivariate diagonal BEKK model, and also to examine some novel interpretations of volatility spillover effects, as established in Chang et al. (2015).

The paper not only considers the widely-used hedging instrument, namely, futures, but also takes an interesting new hedging instrument, ETF, into account. ETF is regarded as index futures when investors manage their portfolios, the hedging method can be calculated by using correlations or covariances to calculate an optimal dynamic hedging ratio. This is a very useful and interesting application for the estimation and testing of volatility spillovers.

In the empirical analysis, diagonal BEKK models with different sizes of the weighting matrix A are considered and estimated for comparing patterns of volatility spillovers. The paper provided a new way of analyzing and describing the patterns of volatility spillovers, which should be useful for the future empirical analysis of estimating and testing volatility spillover effects.

These results suggest that volatility spillovers exist for all four kinds of financial assets in three different markets, though there are some differences in the quantitative results. For example, there is greater asymmetry of signs in the results of the 12 x 12 matrix as there are more negative mean return shocks. The differences might be caused by adding too many variables in the weighting matrix, while most of the results for fixed i and j in the 3 x 3 and 4 x 4 matrices are still broadly similar, as are most of the signs of the mean return shocks.

Adding more variables in the diagonal BEKK model means that the number of iterations for convergence can increase sharply and reach the default option too easily. Therefore, it might be more appropriate to try a smaller weighting matrix A, and focus on more specific combinations, such as three or four assets in each market.

For a further discussion of applying the results of volatility spillovers, the optimal dynamic hedging ratio, which can be presented as $\beta_{ij,t} = \frac{Q_{ij,t}}{Qii,t}$, $Q_{ij,t}$ is the conditional covariance of i and j, and $Q_{ii,t}$ is the condtional variance of i. As the covolitility spillovers effect can measure the changes in the conditional covariances, not only the mean hedge ratio can be calculated, but it is also possible to apply the spillovers for dynamic hedging. This type of application could possibly be a new and useful direction for further research.

Table 1

Variable Definitions

Variable	Definition	Data Source or Transactions Market	Description
$Corn_s$	Corn spot return	U.S. Department of Agriculture (USDA)	Corn Number 2 Yellow
$Corn_f$	Corn futures return	Chicago Board of Trade (CBOT)	CBOT - Corn Continuous
$Corn_i$	Corn index return	NYSE Arca	Teucrium Corn Fund Benchmark Index
$Corn_e$	Corn ETF return	NYSE Arca	Teucrium Corn Fund
$Sugar_s$	Sugar spot return	U.S. Department of Agriculture (USDA)	Raw Sugar - International Sugar Agreement (ISA)
$Sugar_f$	Sugar futures return	Coffee, Sugar & Cocoa Exchange (CSCE)	CSCE - Sugar # 11
$Sugar_i$	Sugar index return	NYSE Arca	Bloomberg Sugar Subindex Total Return
$Sugar_e$	Sugar ETF return	NYSE Arca	iPath Bloomberg Sugar Subindex Total Return ETN
$Ethanol_s$	Ethanol spot return	Bloomberg	Bloomberg Ethanol Prompt mth fob spot price/Chicago
$Ethanol_f$	Ethanol futures return	Chicago Board of Trade (CBOT)	eCBOT - Ethanol Continuous
$Ethanol_i$	Ethanol index return	NYSE Arca	BofA MLCX Biofuels Total Return Index
$Ethanol_e$	Ethanol ETF return	NYSE Arca	ELEMENTS Linked to the MLCX Biofuels Index Total Return IOPV

Table 2
Descriptive Statistics

	Mean	SD	Max	Min	Skewness	Kurtosis	Jarque-Bera
$Corn_s$	0.008	1.78	9.305	-8.692	0.0095	5.8693	524.867
$Corn_f$	0.007	1.843	8.618	-24.529	-1.485	25.219	32033.9
$Corn_i$	0.007	1.503	7.463	-6.121	0.205	5.264	337.464
$Corn_e$	-0.011	1.573	13.632	-9.126	0.465	9.595	2827.868
$Sugar_s$	-0.003	1.837	9.792	-13.016	-0.423	8.565	2019.985
$Sugar_f$	-0.006	2.046	10.457	-12.366	-0.286	7.052	1067.439
$Sugar_i$	-0.011	1.898	8.558	-12.365	-0.294	6.604	849.854
$Sugar_e$	-0.016	1.979	7.718	-13.059	-0.241	6.141	643.888
$Ethanol_s$	-0.004	2.663	20.605	-22.525	-0.731	20.255	19117.570
$Ethanol_f$	-0.001	2.152	9.403	-21.566	-2.601	25.201	33147.840
$Ethanol_i$	0.011	1.102	5.481	-6.236	-0.070	5.766	488.936
$Ethanol_e$	0.008	1.113	6.311	-6.143	0.008	6.009	577.360

Note: The Jarque-Bera Lagrange Multiplier test is asymptotically chi-squared, and is based on testing skewness and kurtosis against the normal distribution.

Table 3

Unit Root Tests

	no trend and intercept		with intercept		with trend and intercept	
Variables	**ADF test**	**PP test**	**ADF test**	**PP test**	**ADF test**	**PP test**
$Corn_s$	-38.491*	-38.606*	-38.479*	-38.595*	-38.569*	-38.645*
$Corn_f$	-38.778*	-38.779*	-38.766*	-38.767*	-38.831*	-38.837*
$Corn_i$	-39.308*	-39.324*	-39.296*	-39.312*	-39.412*	-39.451*
$Corn_e$	-41.394*	-41.438*	-41.382*	-41.427*	-41.501*	-41.582*
$Sugar_s$	-41.358*	-41.351*	-41.345*	-41.338*	-41.343*	-41.337*
$Sugar_f$	-39.734*	-39.733*	-39.721*	-39.721*	-39.716*	-39.715*
$Sugar_i$	-39.738*	-39.737*	-39.726*	-39.725*	-39.785*	-39.784*
$Sugar_e$	-40.655*	-40.629*	-40.643*	-40.618*	-40.703*	-40.684*
$Ethanol_s$	-36.041*	-36.144*	-36.029*	-36.133*	-36.041*	-36.135*
$Ethanol_f$	-27.726*	-33.123*	-27.716*	-33.111*	-27.746*	-33.112*
$Ethanol_i$	-37.681*	-37.712*	-37.672*	-37.704*	-37.771*	-37.782*
$Ethanol_e$	-37.875*	-37.917*	-37.865*	-37.907*	-37.962*	-37.976*

Note: * denotes the null hypothesis of a unit root is rejected at the 1% level.

Table 4

Price Correlations

	$Corn_s$	**$Corn_f$**	**$Corn_i$**	**$Corn_e$**	**$Sugar_s$**	**$Sugar_f$**	**$Sugar_i$**	**$Sugar_e$**	**$Ethanol_s$**	**$Ethanol_f$**	**$Ethanol_i$**	**$Ethanol_e$**
$Corn_s$	1											
$Corn_f$	0.9839	1										
$Corn_i$	0.9488	0.9398	1									
$Corn_e$	0.9686	0.9742	0.9705	1								
$Sugar_s$	0.6667	0.7117	0.5805	0.7270	1							
$Sugar_f$	0.6284	0.6777	0.5294	0.6853	0.9923	1						
$Sugar_i$	0.8033	0.8260	0.7535	0.8609	0.9492	0.9254	1					
$Sugar_e$	0.8006	0.8246	0.7477	0.8592	0.9522	0.9295	0.9996	1				
$Ethanol_s$	0.7435	0.7341	0.7958	0.8088	0.6594	0.6113	0.7610	0.7580	1			
$Ethanol_f$	0.8627	0.8565	0.8668	0.8951	0.7316	0.6828	0.8271	0.8249	0.9420	1		
$Ethanol_i$	0.8894	0.8874	0.9498	0.9364	0.6919	0.6400	0.8347	0.8284	0.8411	0.8886	1	
$Ethanol_e$	0.8982	0.8993	0.9474	0.9474	0.7243	0.6747	0.8594	0.8541	0.8463	0.8976	0.9983	1

Table 5

Return Correlations

	$Corn_s$	$Corn_f$	$Corn_i$	$Corn_e$	$Sugar_s$	$Sugar_f$	$Sugar_i$	$Sugar_e$	$Ethanol_s$	$Ethanol_f$	$Ethanol_i$	$Ethanol_e$
$Corn_s$	1											
$Corn_f$	0.8655	1										
$Corn_i$	0.8766	0.8855	1									
$Corn_e$	0.8223	0.8439	0.9559	1								
$Sugar_s$	0.1663	0.1651	0.1825	0.1842	1							
$Sugar_f$	0.1992	0.2051	0.2360	0.2310	0.7109	1						
$Sugar_i$	0.2212	0.2398	0.2574	0.2574	0.7060	0.9308	1					
$Sugar_e$	0.2302	0.2508	0.2653	0.2716	0.6899	0.8987	0.9630	1				
$Ethanol_s$	0.2548	0.2270	0.2434	0.2297	0.0429	0.0612	0.0635	0.0595	1			
$Ethanol_f$	0.5020	0.4926	0.5137	0.5077	0.1215	0.1320	0.1685	0.1685	0.5398	1		
$Ethanol_i$	0.7286	0.7353	0.8092	0.7829	0.4085	0.5326	0.5805	0.5725	0.2190	0.4523	1	
$Ethanol_e$	0.7080	0.7119	0.7835	0.7337	0.4093	0.5143	0.5633	0.5621	0.2125	0.4318	0.9644	1

Table 6

Diagonal BEKK and Mean Return Shocks for Stocks and Agricultural Commodities

(12 x 12 Portfolio)

	A(i,i)	$\overline{\hat{\varepsilon}_{\iota}}$
$Corn_s$	0.216967	0.008851
$Corn_f$	0.238958	-0.003618
$Corn_i$	0.227925	0.007917
$Corn_e$	0.258604	-0.048105
$Sugar_s$	0.317321	0.017184
$Sugar_f$	0.290613	0.046445
$Sugar_i$	0.227946	0.030713
$Sugar_e$	0.219313	0.028441
$Ethanol_s$	0.259134	-0.032301
$Ethanol_f$	0.339403	-0.03359
$Ethanol_i$	0.219893	-0.000463
$Ethanol_e$	0.209927	0.013406

Table 7

Scalar and Diagonal BEKK and Signs of Return Shocks (12 x 12 Portfolio)

Asset / $\overline{\varepsilon}_t$	**Corn$_s$**	**Corn$_f$**	**Corn$_i$**	**Corn$_e$**	**Sugar$_s$**	**Sugar$_f$**	**Sugar$_i$**	**Sugar$_e$**	**Ethanol$_s$**	**Ethanol$_f$**	**Ethanol$_i$**	**Ethanol$_e$**
Corn$_s$												
Corn$_f$	{D,A_{sym}}											
Corn$_i$	{D,S_{ym}}	{D,A_{sym}}										
Corn$_e$	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}									
Sugar$_s$	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}								
Sugar$_f$	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}							
Sugar$_i$	{D,S_{ym}}	{D,A_{sym}}	{S,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,S_{ym}}						
Sugar$_e$	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,S_{ym}}	{D,S_{ym}}					
Ethanol$_s$	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{S,S_{ym}}	{D,A_{sym}}	{D,A_{sym}}	{D,A_{sym}}	{D,A_{sym}}				
Ethanol$_f$	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,A_{sym}}	{D,A_{sym}}	{D,A_{sym}}	{D,S_{ym}}			
Ethanol$_i$	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,A_{sym}}	{D,A_{sym}}	{S,A_{sym}}	{D,S_{ym}}	{D,S_{ym}}		
Ethanol$_e$	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,A_{sym}}	{D,S_{ym}}	{D,S_{ym}}	{D,S_{ym}}	{D,S_{ym}}	{D,A_{sym}}	{D,A_{sym}}	{D,A_{sym}}	

Note: On the left side of each entry, S (D) denotes scalar (diagonal) multipliers. On the right side of each entry, S_{ym} (A_{sym}) denotes symmetry (asymmetry) in sign.

Table 8

Scalar and Diagonal BEKK and Signs of Return Shocks (2 x 2 Pairs)

Asset / $\bar{\hat{\varepsilon}}_t$	**Corn$_s$**	**Corn$_f$**	**Corn$_i$**	**Corn$_e$**	**Sugar$_s$**	**Sugar$_f$**	**Sugar$_i$**	**Sugar$_e$**	**Ethanol$_s$**	**Ethanol$_f$**	**Ethanol$_i$**	**Ethanol$_e$**
Corn$_s$												
Corn$_f$	{D,S$_{ym}$}											
Corn$_i$	{S,A$_{sym}$}	{S,S$_{ym}$}										
Corn$_e$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}									
Sugar$_s$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}								
Sugar$_f$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}							
Sugar$_i$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}						
Sugar$_e$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{S,S$_{ym}$}					
Ethanol$_s$	{D,A$_{sym}$}	{D,A$_{sym}$}	{D,A$_{sym}$}	{D,A$_{sym}$}	{D,A$_{sym}$}	{D,A$_{sym}$}	{D,A$_{sym}$}	{D,A$_{sym}$}				
Ethanol$_f$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{S,A$_{sym}$}			
Ethanol$_i$	{D,S$_{ym}$}	{D,S$_{ym}$}	{S,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,A$_{sym}$}	{D,S$_{ym}$}		
Ethanol$_e$	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	{D,A$_{sym}$}	{D,S$_{ym}$}	{D,S$_{ym}$}	

Note: On the left side of each entry, S (D) denotes scalar (diagonal) multipliers. On the right side of each entry, S$_{ym}$ (A$_{sym}$) denotes symmetry (asymmetry) in sign.

Table 9

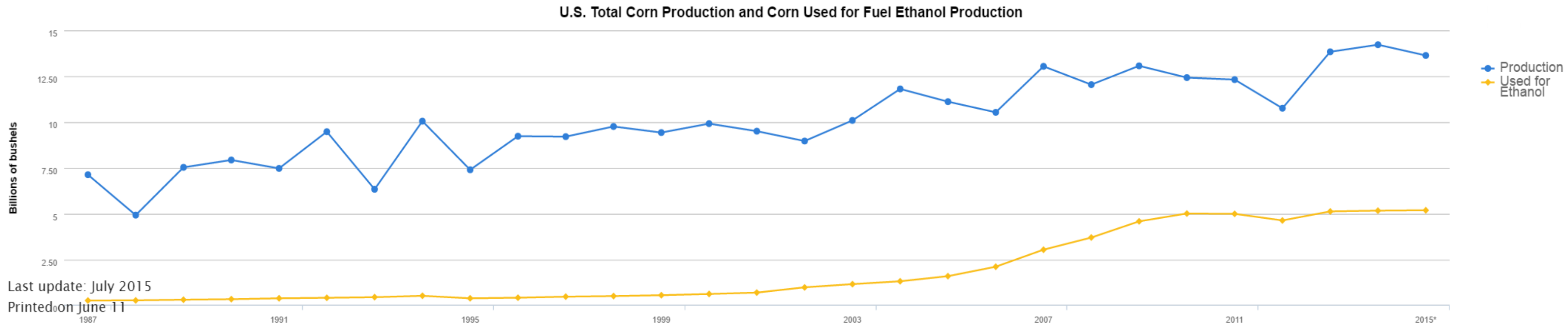
Patterns of Spillovers for 2 x 2 Pairs and 12 x 12 Portfolio

	Corn$_s$	**Corn**$_f$	**Corn**$_i$	**Corn**$_e$	**Sugar**$_s$	**Sugar**$_f$	**Sugar**$_i$	**Sugar**$_e$	**Ethanol**$_s$	**Ethanol**$_f$	**Ethanol**$_i$	**Ethanol**$_e$
Corn$_s$												
Corn$_f$	{Y,N}											
Corn$_i$	{N,Y}	{N,N}										
Corn$_e$	{Y,N}	{Y,N}	{Y,N}									
Sugar$_s$	{Y,Y}	{Y,N}	{Y,Y}	{Y,N}								
Sugar$_f$	{Y,Y}	{Y,N}	{Y,Y}	{Y,N}	{Y,Y}							
Sugar$_i$	{Y,Y}	{Y,N}	{N,Y}	{Y,N}	{Y,Y}	{N,Y}						
Sugar$_e$	{Y,Y}	{Y,N}	{Y,Y}	{Y,N}	{Y,Y}	{Y,Y}	{Y,Y}					
Ethanol$_s$	{Y,Y}	{Y,N}	{Y,Y}	{N,N}	{Y,N}	{Y,N}	{Y,N}	{N,N}				
Ethanol$_f$	{Y,N}	{Y,Y}	{Y,N}	{Y,Y}	{Y,N}	{Y,N}	{N,N}	{Y,N}	{N,N}			
Ethanol$_i$	{Y,N}	{Y,Y}	{N,N}	{Y,Y}	{Y,Y}	{Y,Y}	{Y,Y}	{Y,Y}	{Y,N}	{Y,Y}		
Ethanol$_e$	{Y,Y}	{Y,N}	{Y,Y}	{Y,N}	{Y,Y}	{N,Y}	{Y,Y}	{N,N}	{Y,Y}	{Y,N}	{Y,N}	

Note: On the left side of each entry, Y (N) denotes there is (not) a similarity of patterns in multipliers. On the right side of each entry, entry, Y (N) denotes there is (not) a similarity of patterns in signs.

Figure 1

Corn Production and Corn Used for Fuel Ethanol Production in USA



Source: USDA's National Agriculture Statistics Service database query

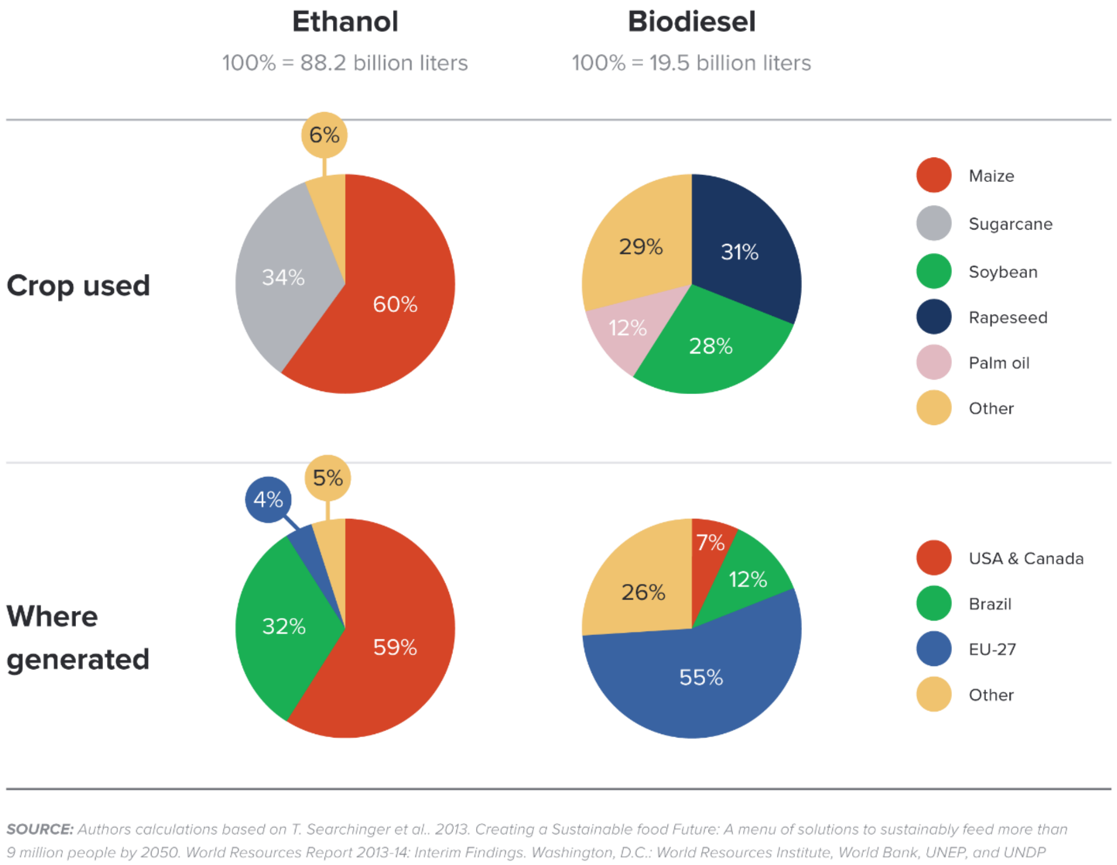
Notes: *2015 values are preliminary.

This chart shows total U.S. corn production and corn used to produce fuel ethanol from 1987 to 2015. The overall trend has been one of increasing production. The amount of corn used for ethanol production increased substantially between 2001 and 2010, owing primarily to federal laws and incentives that aim to increase energy security and reduce vehicle emissions. The increased ethanol seems to have come from the increase in overall corn production and a small decrease in corn used for animal feed and other residual uses. The amount of corn used for other uses including human consumption has stayed consistent from year to year. This long-term trend even held true during the drought of 2012 when production, ethanol usage, and feed usage all decreased substantially but other usage held steady.

U.S. DEPARTMENT OF ENERGY | Energy Efficiency & Renewable Energy   Source: Alternative Fuels Data Center

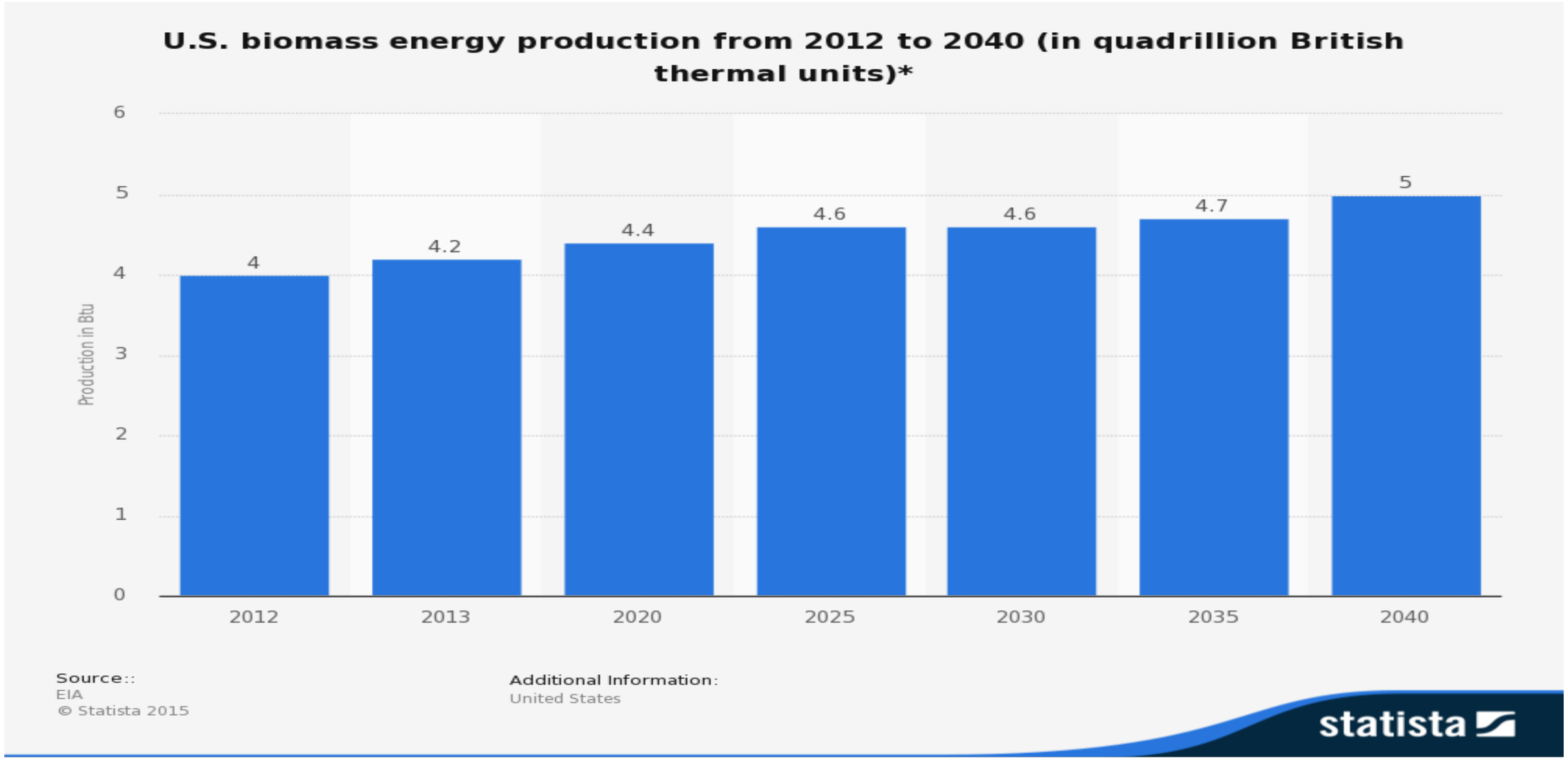
Source: U.S. Department of Energy

Figure 2
Biomass Energy Sources and Places of Production



Source: Authors calculations based on T. Searchinger et al. (2013). Creating a Sustainable food Future: A menu of solutions to sustainably feed more than 9 million people by 2050. World Resources Report 2013-14: Interim Findings. Washington, D.C. World Resources Institute, World Bank, UNEP and UNDP.

Figure 3
US Biomass Energy Production



Source: Statista collected from U.S. Energy Information Administration

Figure 4
Corn, Sugar, and Ethanol for Spot, Futures, Index, and ETF Returns

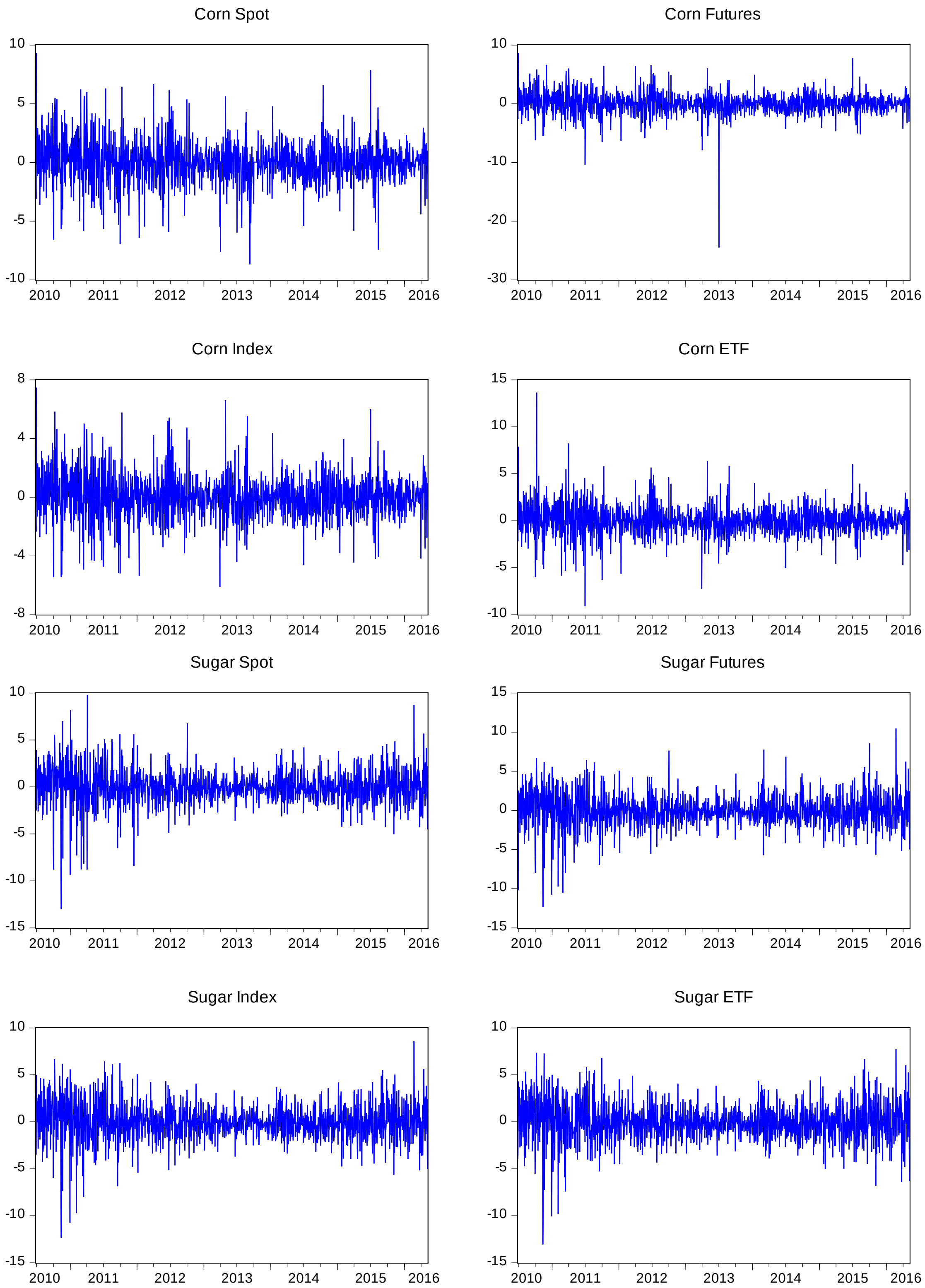
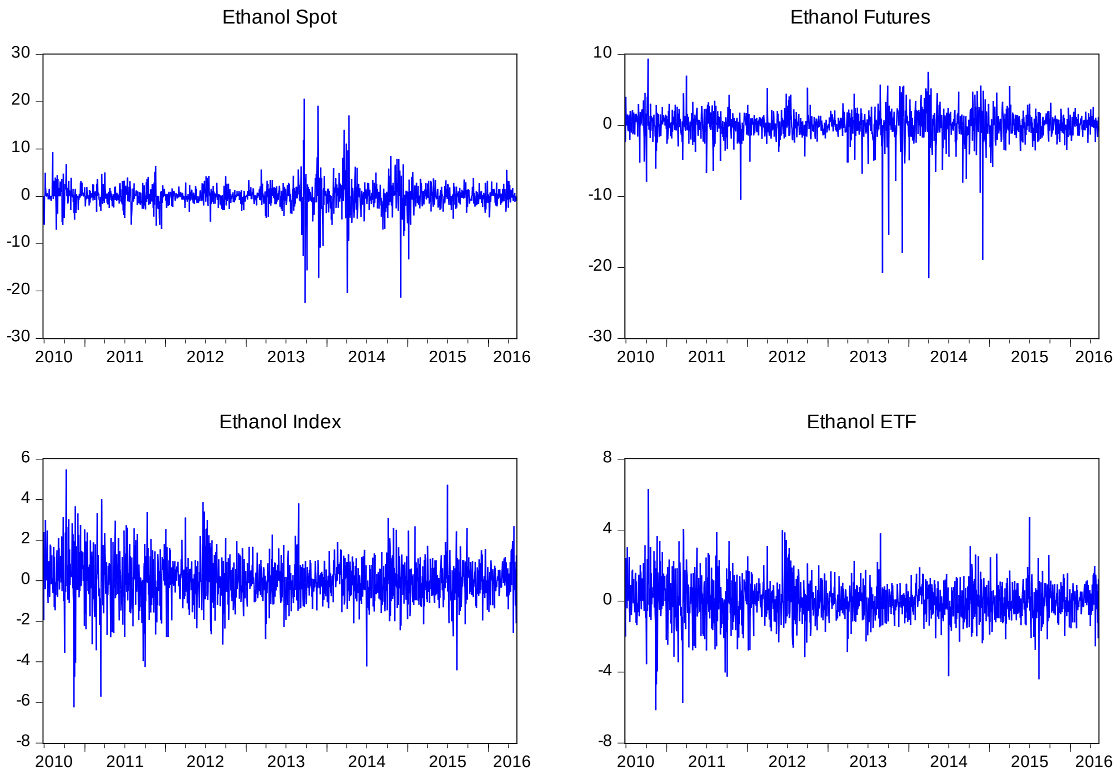


Figure 4 (cont.)

Corn, Sugar, and Ethanol for Spot, Futures, Index, and ETF Returns



References

Aielli, G.P. (2013), Dynamic conditional correlations: On properties and estimation, Journal of Business and Economic Statistics, 31, 282-299.

Ajanovic, A. (2011), Biofuels versus food production: Does biofuels production increase food prices?, Energy, 36(4), 2070-2076.

Algieri, B. (2014), The influence of biofuels, economic and financial factors on daily returns of commodity futures prices, Energy Policy, 69, 227-247.

Baba, Y., R.F. Engle, D. Kraft and K.F. Kroner (1985), Multivariate simultaneous generalized ARCH. Unpublished manuscript, Department of Economics, University of California, San Diego, CA, USA.

Bollerslev, T. (1986), Generalised autoregressive conditional heteroscedasticity, Journal of Econometrics, 31, 307-327.

Bollerslev, T. (1990), Modelling the coherence in short-run nominal exchange rate: A multivariate generalized ARCH approach, Review of Economics and Statistics, 72, 498-505.

Bollerslev, T., R. Engle and J. Wooldridge (1988), A capital asset pricing model with time varying covariance, Journal of Political Economy, 96, 116-131.

Caporin, M. and M. McAleer (2013), Ten things you should know about the dynamic conditional correlation representation, Econometrics, 1(1), 115-126.

Chang, C.-L., L.-H. Chen, S. Hammoudeh and M. McAleer (2012), Asymmetric adjustments in the ethanol and grains markets, Energy Economics, 34(6), 1990-2002.

Chang, C-L., T.-L. Hsieh and M. McAleer (2016), How are VIX and stock index ETF related?, Tinbergen Institute Discussion Papers, 16-010/III, The Netherlands.

Chang, C.-L., Y.-Y. Li and M. McAleer (2015), Volatility spillovers between energy and agricultural markets: A critical appraisal of theory and practice, Tinbergen Institute Discussion Papers, 15-077/III, The Netherlands.

Chang, C.-L., M. McAleer and R. Tansuchat (2009), Modelling conditional correlations for risk diversification in crude oil markets, Journal of Energy Markets, 2(4), 29-51.

Chang, C.-L., M. McAleer and R. Tansuchat (2010), Analyzing and forecasting volatility spillovers, asymmetries and hedging in major oil, Energy Economics, 32(6), 1445-1455.

Chang, C.-L., M. McAleer and R. Tansuchat (2011), Crude oil hedging strategies using dynamic multivariate GARCH, Energy Economics, 33(5), 912-923.

Chang, C.-L., M. McAleer and Y.-A. Wang (2016), Modelling volatility spillovers for bio-ethanol, sugarcane and corn, Tinbergen Institute Discussion Papers 16-014/III, The Netherlands.

Chen J.-H. and C.-Y. Huang (2010), An analysis of the spillover effects of exchange traded funds, Applied Economics, 42(9), 1155-1168.

Du, X. and D.J. Hayes (2009), The impact of ethanol production on US and regional gasoline markets, Energy Policy, 37(8), 3227–3234.

Du, X. and L.L. McPhail (2012), Inside the black box: The price linkage and transmission between energy and agricultural markets, Energy Journal, 33(2), 171-194.

Engle, R.F. (1982), Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, Econometrica 50, 987-1007.

Engle, R.F. (2002), Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional hereoskedasticity models, Journal of Business and Economic Statistics, 20, 339-350.

Engle, R.F. and K.F. Kroner (1995), Multivariate simultaneous generalized ARCH, Econometric Theory, 11(1), 122-150.

Hafner, C. and M. McAleer (2014), A one line derivation of DCC: Application of a vector random coefficient moving average process, Tinbergen Institute Discussion Paper 14-087, The Netherlands.

Ling, S. and M. McAleer (2003), Asymptotic theory for a vector ARMA-GARCH model, Econometric Theory, 19, 278-308.

Manera, M., M. McAleer and M. Grasso (2006), Modelling time-varying conditional correlations in the volatility of Tapis oil spot and forward returns, Applied Financial Economics, 16(7), 525-533.

McAleer, M. (2005), Automated inference and learning in modeling financial volatility, Econometric Theory, 21(1), 232-261.

McAleer, M., F. Chan, S. Hoti and O. Lieberman (2008), Generalized autoregressive conditional correlation, Econometric Theory, 24(6), 1554-1583.

McAleer, M., S. Hoti and F. Chan (2009), Structure and asymptotic theory for multivariate asymmetric conditional volatility, Econometric Reviews, 28, 422-440.

McPhail, L.L. and B.A. Babcock (2012), Impact of US biofuel policy on US corn and gasoline price variability, Energy, 37(1), 505-513.

Newman, J. (2016, April 12), Grain prices rise even as stockpiles climb, The Wall Street Journal.

Poterba, J.M. and J.B. Shoven (2002), Exchange traded funds: A new investment option for taxable investors, American Economic Review, 92, 422-427.

Rathmann, R., A. Szklo and R. Schaeffer (2010), Land use competition for production of food and liquid biofuels: An analysis of the arguments in the current debate, Renewable Energy, 35(1), 14-22.

Serra T. and D. Zilberman (2013), Biofuel-related price transmission literature: A review, Energy Economics, 37, 141-151.

Trujillo-Barrera, A., M.L. Mallory and P. Garcia (2012), Volatility spillovers in US crude oil, ethanol and corn futures markets, Journal of Agricultural and Resource Economics, 37(2), 247262.

Tsay, R.S. (1987), Conditional heteroscedastic time series models, Journal of the American Statistical Association, 82, 590-604.

Tse, Y.K. and A.K.C. Tsui (2002), A multivariate GARCH model with time-varying correlations, Journal of Business and Economic Statistics, 20, 351-362