ETHANOL HEDGING STRATEGIES USING DYNAMIC MULTIVARIATE GARCH

Introduction

The total domestic production of ethanol in the United States has had tremendous growth as an alternative energy product since the turn of the century. The annual production in the United States increased almost threefold from 4,884 million gallons per year in 2006 to 13,218 million gallons per year in 2012(Renewable Fuels Association 2014b). Along with this growth, ethanol's reputation as a commodity has developed a young but maturing futures market whose volume and open interest has similarly continued to grow.

The purpose of this paper is to construct hedge ratios for ethanol futures derivatives using constant and dynamic multivariate GARCH models. Hedge ratios are important data points for ethanol producers and consumers that allow these market participants to optimally lower their risk exposure to price fluctuations in the underlying spot price. In this paper, conditional and dynamic multivariate GARCH models are used to create risk minimizing portfolios which can then be tested to identify appropriate hedge ratios, optimal portfolio weights and efficient hedge portfolios. The principal idea behind hedging strategies is to create a combination of investments in the spot and futures markets of a commodity to form a portfolio that serves to reduce risk by managing the prices of the commodity given future fluctuations in price.

Due to the 2005 Energy Policy Act (EPAct) which established standards to blend ethanol into the U.S. gasoline supply, nearly all gasoline in the U.S. contains up to 10% ethanol. Ethanol is used as an oxygenate which is a gasoline additive that reduces carbon monoxide. In addition to environmental motivations, the passage of the EPAct was motivated by the perceived ability of ethanol to decrease the pressure on U.S. importation of foreign oil.

As the market for ethanol continues to grow and the market for ethanol futures increases in volume and activity, ethanol producers and consumers are increasingly interested in managing risk for production and consumption given fluctuations in energy commodity prices. Risk in the ethanol market can occur from fluctuating supply and demand as well as international production and government regulation. This paper will address the use of multivariate conditional correlation models to create these portfolios.

Literature Review

The purpose of this paper is to test different multivariate methodologies for the existence of multivariate conditional correlations that lead to more efficient hedging strategies for ethanol producers and consumers. Developing hedging strategies usually involves the construction of optimal hedge ratios (OHR) and testing those ratios to construct the most efficient portfolios to lower risk. A common methodology for constructing a hedging strategy is the minimum-variance (MV) hedge ratio originally developed by Leland (1960). Chen *et al.* (2003) provide a review of futures hedge ratios including the MV ratio and alternative methodologies for developing hedge ratios that include ARCH and GARCH models.

Financial asset return volatilities, covariances and correlations have time-varying properties that make linear models inappropriate for modern portfolio construction and are currently constructed using conditional volatility and stochastic volatility models. Multivariate GARCH models are good fits for constructing OHRs because the joint distributions of spot and futures prices vary over time. Dynamic multivariate models take this movement into account and should exhibit greater performance in terms of risk reduction when compared to constant multivariate models.

Energy Market Futures and Hedging

Futures contracts are agreements in which two parties agree to purchase or sell a commodity to each other at a predetermined price at some defined future date. A producer or purchaser of a commodity can use derivatives such as futures contracts to minimize their risk exposure to price fluctuation by hedging with different futures contracts. Speculators attempt to take advantage of the fluctuations in the market by exploring, or exploiting, the price of the futures contract before its maturity. These derivative contracts are useful in managing risk and are commonly used as hedging instruments for other commodities including energy commodities such as oil, gasoline and natural gas. Futures contracts are attractive hedging tools because they are liquid and have low transaction costs.

Multivariate models have had impact in analyzing energy markets and can be used to test for correlations of other related economic markets and indicators. For example, Chevallier (2011) analyzes the time-varying correlations in oil, gas and carbon dioxide (CO_2) prices using multivariate GARCH models and identify dynamic correlations between energy and emissions markets. Research in oil market futures includes the study of volatility on spot and future returns. Lanza *et al.* (2006) estimate DCC-GARCH returns in West Texas Intermediate (WTI) oil futures prices and find that dynamic conditional correlations are time-varying and can vary dramatically. Manera *et al.* (2006) estimate DCC-GARCH on the returns of the Tapis oil spot and one month forward contracts and find that constant conditional correlation is not supported but the dynamic conditional correlations are generally interdependent over time and that they should be considered for sensible hedging strategies. Chang *et al.* (2009) estimate univariate and multivariate returns from three oil markets: WTI, Brent and Dubai. Their results showed statistically significant estimates for the returns of each energy market showing that the constant conditional correlations did not hold.

In addition, Haigh and Holt (2002) use multivariate GARCH methodology on crude oil, heating oil and unleaded gasoline futures to test for their effectiveness in reducing volatility for traders hedging against the crack spread. The crack spread is the difference in price between the primary resource, or price at the well, such as crude oil and the price of the refined commodity, such as heating oil or gasoline. They find that the assumption of independence between commodities in the crack spread is erroneous and that crack spread traders should take co-movements into account when calculating hedging strategies for risk reduction.

Once conditional correlations are calculated, covariates and correlations can be used to calculate OHRs, portfolio weights and optimum hedge portfolios. For example, Jalali-Naini and Manesh (2006) use a GARCH-M model to construct optimal hedge portfolios for crude oil and find that the perceived risk and OHR increase with the length of the contract. Chang *et al.* (2010) estimated OHR and optimal portfolio weights of crude oil portfolios using VARMA-GARCH but focused on the spillover effects in the returns of the spot, forward and futures markets.

Chang *et al.* (2011) estimate several multivariate volatility models to test the OHR for the crude oil spot and futures returns for two benchmark international crude oil markets, WTI oil and Brent oil. They further constructed the portfolio weights and tested each in terms of lowering risk. They found that the optimal portfolio weights for both Brent and WTI markets of all multivariate models suggested holding futures in greater proportions than spot holdings with the exception of the WTI BEKK model which recommended holding spot in greater proportion to futures. BEKK models are dynamic conditional models that have positive definite conditional covariance matrices.

Ethanol Spot and Futures Market

Ethanol production in the United States increased sevenfold between 2000 and 2012. Additional signals that the ethanol market is maturing include increased government regulation of ethanol, growth in the number of producers and the development of a growing futures market. The total domestic production grew from 1,622 million gallons per year in 2000 to 13,218 million gallons in 2012. That increase reflects a growth of 8 times the size of the total production from the turn of the century and is reflective of the growing importance of the ethanol market in the U.S.

Trujillo-Barrera *et al.* (2011) measure the volatility spillover from crude oil to the corn and ethanol markets and unlike Zhang *et al.* (2009), they find that the oil market has a strong volatility spillover to ethanol and corn markets. Additionally, other papers find similar results that describe the increasingly strengthened relationship between oil, corn, soybean and ethanol markets (Auld 2012; Hochman *et al.* 2012; Elmarzougui & Larue 2013; Natanelov *et al.* 2013). Dahlgran (2009) finds that hedging in the corn crushing (ethanol) market is effective only in longer terms. In addition, ethanol futures are more efficient than gasoline futures for hedging risk.

Pokrivčák and Rajčaniová (2011) use VAR methodology to test the statistical relationship between ethanol, gasoline and crude oil prices in Europe. They find that ethanol, gasoline and crude oil are not co-integrated but that first differences do show an impact on each other's prices primarily in the oil and gasoline relationship.

Data and Methodology

The data for this paper was obtained from the CME Group data as listed in the Datastream database and constructed from weekly data from June 2006 to June 2014. Further monthly data for production and stock storage was obtained from the Renewable Fuels Association (Renewable Fuels Association 2014a) and used for descriptive purposes. This study uses multivariate GARCH methodologies to identify correlations and covariates between spot and futures prices of ethanol.

Descriptive Statistics

The time periods for this sample are from March 2006 until the end of 2013 and reflect the time period that the ethanol futures contract was available for trading according to data from Datastream. The futures data for ethanol is taken from the Chicago Board of Trade (CBOT) futures derivative. This work includes three U.S. based spot prices which include the New York Harbor (NY) spot price, the Chicago (CHI) spot price and the Gulf Coast (GULF) spot price.

Following a traditional approach, we construct returns for spot and futures time series as the first difference of the natural log of each value. The returns are expressed as percentages:

$$r_t = [\ln(p_t) - \ln(p_{t-1})] \times 100 \tag{1}$$

where p_t and p_{t-1} are the price levels of a time series variable at time *t*.

The summary statistics for spot and future returns are presented in Table 1, which report information on the mean, standard deviation, skewness, kurtosis and the Ljung-Box test for the sample.

[Table 1]

Table 1 contains the descriptive statistics for ethanol futures and spot prices and returns. Specifically, we report mean, standard deviation, min/max, skewness, kurtosis and the Ljung-Box test. The mean values for ethanol futures prices is 2.139, which is slightly lower than the means of each of the spot prices. Returns are calculated in terms of percentages and future returns have a mean of -0.144.

The New York and Gulf Coast ethanol spot prices have zero skewness and kurtosis. However, the Chicago ethanol spot price exhibits some positive skewness, 0.185, and kurtosis 0.856. These moments describe a distribution curve of the Chicago ethanol prices and having a higher peak than normal and slight lean toward observations lower than the median. The extreme *minimum* and *maximum* values present in the returns of Chicago ethanol spot price may be a result of this skewness and kurtosis. It is important to construct different hedging portfolios for each of the regional spot prices such that geographic presence of any market participant is more adequately calculated.

Furthermore, prices for both spot and futures appear to exhibit autocorrelation as suggested by the Ljung-Box test statistic. The Ljung-Box test on returns does not show autocorrelation effects, with the exception of the Chicago spot price.

[Figure 1]

Figure 2 displays the weekly prices and returns for ethanol futures and spot derivatives. As expected, a visual inspection of the data over time shows that the spot and futures prices are highly correlated. The volatility of the futures returns appears to be more volatile than spot returns. There appears not to be great deviation in volatility between the returns of the three spot commodities with the exception of the singular volatility event in late 2013.

[Table 2]

Table 2 displays the correlation coefficients for ethanol futures and three U.S. based spot prices that differ based on geographic markets: New York Harbor, Chicago and Gulf Coast. As expected, correlations between the three spot prices are high. In terms of diversification, the correlation scores over .9 are indications that the ethanol futures derivative is a good tool for constructing hedging strategies. In addition to the regional application of separate hedging strategies dependent on the ethanol spot price in a market participant's region, the three ethanol prices are included in this report as a robustness check to ensure that results are consistent over different regional markets.

[Table 3]

We test these series for unit roots to ensure that each series is stationary. It is important to ensure that the tested series are stationary to avoid spurious results. The null hypothesis for the unit root tests is that the series have a unit root. Significant results signal that the series are stationary. We use multiple unit root tests in the table because of the mixed results in the price level of these tests.

The ADF, DF-GLS and Phillips-Peron unit root tests in Table 3 show mixed results for ethanol prices with the DF-GLS showing results that are not statistically significant, signaling that they contain a unit root. However, all tests are statistically significant for returns in all four series, which are the variables used for the conditional correlation models.

Econometric Models

This section describes the principal econometric models designed to report the interdependence between the spot and futures prices and how it evolves over time. This paper presents two econometric models, the Constant Conditional Correlation (CCC) GARCH model of Ling and McAleer (2003), and the Dynamic Conditional Correlation Model of Engle (2002).

The mean equation estimated uses the lags of both the futures return and the return of the specified spot price:

$$r_t = \gamma_0 + \gamma_1 r_{F,t-1} + \gamma_2 r_{S,t-1} + \varepsilon_t \tag{2}$$

where r_t is the return of the time series being evaluated.

The CCC-GARCH model assumes that the conditional variance of the returns follows a univariate GARCH(p,q) process:

$$h_{it} = \varpi_i + \sum_{j=1}^{p} \alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{q} \beta_{ij} h_{i,t-j}, \tag{3}$$

where α_{ij} represents the ARCH effects, or short run persistence of shocks to the returns, and β_{ij} represents the GARCH effects, or contribution of such shocks to the long-run persistence

$(\alpha_{ij} + \beta_{ij})$. The CCC assumes the independence of conditional variances across returns and hence, no spillovers in volatility across different time series. Further the CCC does not take into account the possibility of asymmetric effects of positive and negative shocks on conditional volatility. Thus the model assumes that positive and negative effects have the same impact on the conditional variance.

The DCC-GARCH model, proposed by Engle (2002) can be superior to the CCC-GARCH model because it assumes that the conditional correlations change over time. The DCC-GARCH involves a two stage estimation of the conditional covariance matrix H_t. The first stage requires the selection of appropriate univariate GARCH models, to obtain the standard deviations, $\sqrt{h_{ii,t}}$. In the second stage, stock return residuals adjust by their estimated standard deviations from the first stage, $u_{it} = \varepsilon_{it}/\sqrt{h_{ii,t}}$, then u_{it} is used to estimate the parameters of conditional correlation. The multivariate conditional variance (the dynamic conditional correlations) is specified as:

$$H_t = D_t R D_t, \tag{4}$$

where D_t is the $(n \times n)$ diagonal matrix of time-varying standard deviation from univariate GARCH models with the standard deviations, $\sqrt{h_{ii,t}}$, on the *i*th diagonal*;* R_t is the $(n \times n)$ time-varying correlation matrix.

The correlation in the DCC model is given by:

$$Q_t = (1 - a - b)\bar{Q} + a u_{t-1} u'_{t-1} + b Q_{t-1} \tag{5}$$

where $Q_t = (q_{ij,t})$ is the $n \times n$ time varying covariance matrix of u_t, $\bar{Q} = E(u_t u'_t)$ is the $n \times n$ unconditional variance matrix of u_t, and a and b are nonnegative scalar parameters satisfying (a+b) < 1. Then it is necessary to re-escalate the matrix Q_t in order to guarantee that all the elements in the diagonal be equal to one. As a result, we obtain a proper correlation matrix R_t.

$$R_t = (diag(Q_t))^{-\frac{1}{2}} Q_t (diag(Q_t))^{-1/2}, \tag{6}$$

where $(diag(Q_t))^{-\frac{1}{2}} = diag(1/\sqrt{q_{11,t}}, \dots, 1/\sqrt{q_{nn,t}})$.

A typical element of R_t is of the form:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \times q_{jj,t}}} \tag{7}$$

The DCC model can be estimated by using a two-stage approach to maximize the log-log-likehood function. Let θ denote the parameters in D_t, and ϕ the parameters in R_t, and then the log-likehood is

$$l_t(\theta, \phi) = \left[-\frac{1}{2} \sum_{t=1}^{T} (nlog(2\pi) + log|D_t|^2 + \varepsilon_t' D_t^{-2} \varepsilon_t) \right] \tag{8}$$

$$+\left[-\frac{1}{2}\sum_{t=1}^{T}(log\,|R_t| + u_t' R_t^{-1} u_t - u_t u'_t)\right]$$

The first part of the likelihood function in equation (8) is volatility, which is the sum of individual GARCH likelihoods. The log-likelihood function can be maximized in the first stage over the parameters in D_t. Given the estimated parameters in the first stage, the correlation component of the likelihood function in the second stage, the second part in equation (6), can be maximized to estimate correlation coefficients.

Optimal Hedging Ratio

After discovering the interdependence, the covariate relationships are then applied to construct and evaluate OHRs. The OHRs are then used to construct optimal portfolios for ethanol producers/consumers and tested for risk minimization.

Considering the case of an ethanol producer that wants to protect itself from price fluctuations, the return on the ethanol producer’s portfolio in terms of spot and futures holdings can be denoted as:

$$R_{hedged,t} = R_{S,t} - \delta_t R_{F,t} \,, \tag{9}$$

where $R_{hedged,t}$ is the return on holding the complete portfolio in one time period, $R_{S,t}$ is the return on the spot position, $R_{F,t}$ is the return on the futures position, and δ_t is the hedge ratio. In equation (9), the hedge ratio is the number of future contracts the ethanol producer must sell per unit of spot ethanol they hold.

The variance of the return of the hedged portfolio, conditional on the information set available, was originally introduced by Johnson (1960):

$$var\left(R_{H,t}\middle|\Omega_{t-1}\right) = var\left(R_{S,t}\middle|\Omega_{t-1}\right) - 2\delta_t cov\left(R_{S,t}, R_{F,t}\middle|\Omega_{t-1}\right) + \delta_t^2 var(R_{F,t}|\Omega_{t-1}) \quad (10)$$

where $var\left(R_{S,t}\middle|\Omega_{t-1}\right)$ is the conditional variance of the spot returns, $2\delta_t cov\left(R_{S,t}, R_{F,t}\middle|\Omega_{t-1}\right)$ is the covariance of the spot and future returns, $\delta_t^2 var(R_{F,t}|\Omega_{t-1})$ is the conditional variance of the future returns and Ω_{t-1}represents the information set.

The OHRs are defined as the value of δ_t that minimizes the risk, conditional variance, of the hedged portfolio returns. The partial derivative of Eq. (10) with respect to δ_t yields the following $OHR_{t,}$ conditional on the information set, Ω_{t-1}:

$$\delta_t^* = \frac{cov(R_{S,t}, R_{F,t})}{\mathrm{var}(R_{F,t})} \quad (11)$$

where returns are defined as the logarithmic differences of spot and futures prices.

The conditional covariance matrix can then be obtained from the multivariate conditional volatility models such that the OHR is constructed as:

$$\delta_t^* = \frac{\eta_{SF,t}}{\eta_{F,t}}, \quad (12)$$

where $\eta_{SF,t}$ is the conditional covariance between spot and futures returns and $\eta_{F,t}$ is the conditional variance of future returns.

Once the OHRs are defined, we can compare their performance given different conditional volatility models. A more accurate model of conditional volatility would be expected to be superior in its hedging effectiveness (Ku *et al.* 2007). Hedging effectiveness could be measured by the risk reduction, or variance reduction, for any hedged portfolio when compared to an unhedged portfolio. We can then construct a hedging effectiveness index to compare different models, where the higher values of the hedging effectiveness index indicates higher hedging effectiveness and greater risk reduction:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{hedged}} \tag{13}$$

In addition to a hedged effectiveness index, Chang *et al.* (2011) construct optimal portfolios following the methods of (Kroner & Ng 1998) and (Hammoudeh *et al.* 2010):

$$W_{SF,t} = \frac{\eta_{F,t} - \eta_{SF,t}}{\eta_{S,t} - 2\eta_{SF,t} + \eta_{F,t}} \tag{14}$$

and

$$W_{SF,t} = \begin{cases} 0, & if \quad W_{SF,t} < 0 \\ W_{SF,t}, & if \quad 0 < W_{SF,t} < 1 \\ 1, & if \quad W_{SF,t} > 1 \end{cases} \tag{15}$$

where $W_{SF,t}$ is the weight of the spot in a one dollar portfolio of ethanol spot/futures at time *t*. Inversely, (1-$W_{SF,t}$) is the weight of the futures in a one dollar portfolio of ethanol spot/futures at time *t*.

Results

The CCC-GARCH estimation results are reported in Table 3.4. The results are reported in four sections including the mean equation, the variance equation, the conditional correlation and finally the log-likelihood and model selection criteria. A Lagrange Multiplier test for ARCH errors in each of the models shows that each model follows a GARCH process.

[Table 4]

Each of the three weekly spot price returns (NY, CHI, and GULF) were independently paired with the ethanol futures price returns to compare the results between the three time series. In addition, this methodology will be helpful to identify the regional geographic importance of price fluctuations and differing hedging strategies for producers and consumers that are geographically distinct.

The lags of ethanol futures returns for each of the spot returns in the mean equation are significant and positive which reflects that the spot price is affected by futures price changes in the same direction. In addition, they are significant but negative for their own lags. The variance equation shows that the lagged conditional volatility is significant for all three spot price returns. This is reflective of the appropriateness of the GARCH(1,1) specification. The constant conditional correlations are all significant at the 1% level. The long run persistence ($\alpha + \beta$) of the models are all near 1 showing a long persistence.

Similarly, the three weekly spot price returns were independently paired with the ethanol futures price returns in the DCC-GARCH to compare the results between the three time series.

[Table 5]

The results in the mean equation are similar for all spot prices. Spot prices have a positive and significant relationship with the lags of the futures market and are negative and significant for their own lags. The variance equation shows that the lagged conditional volatility is significant for all three spot price returns.

The multivariate scalar parameters a and b reported as part of the DCC equation in Table 5 are significant, revealing that the correlation has a dynamic component. Wald tests for each spot price returns reject the null hypothesis that $a = b = 0$ at all levels. Furthermore, the results indicate that the volatility persistence measures for the DCC equation ($a + b$) are close to 1 and display high persistence. Only the ethanol spot price for Chicago has a persistence score greater than 1.

In contrast to table 3.4, no conditional correlation statistic is reported because the dynamic nature of the relationship is described in an observation by observation manner and is not designed to be interpreted as a single statistic. Instead, the dynamic conditional correlation is visible in figure 3.3. Figure 3.3 shows the dynamic conditional correlation for each series of returns over the entire sample. The dynamic conditional correlations charted in figure 3.3 are calculated using equation (5) and by employing the *a* and *b* scalar parameters from the DCC estimates.

[Figure 2]

Each series shows a difference in volatility over the sample period and a quick look at the graphs display that New York has the lowest volatility in correlation followed by Gulf returns. The Chicago returns show greater changes in correlation at key points including just before 2010 and just before 2014 where the dynamic conditional correlations have greater negative changes than the other two series.

Following the methodology in Chang *et al.* (2011), optimal portfolio weights, average optimal hedge ratios (OHRs), portfolio variance and hedge effectiveness (HE) values are constructed for each ethanol spot return given its conditional correlation with the ethanol futures returns. The results are displayed in Table 6.

[Table 6]

First, all models suggest that holding proportions of futures in the portfolio provide more efficient portfolios, given the average OHRs of all models are greater than 0.5. Second, the CCC-GARCH models have higher OHRs than the DCC-GARCH models indicating that the constant conditional correlations predict that additional holdings of futures contracts are required to lower portfolio risk.

The HE for all three spot prices is only slightly higher for the CCC-GARCH model indicating that the dynamic conditional correlation is marginally less effective than the DCC-GARCH model. However, since the CCC-GARCH is a reduced form of the DCC-GARCH, the hedging differences are coincidental in this case. The confirmed existence of a DCC-GARCH in Table 3.5 tells us that the correlation between ethanol futures and spot prices are indeed dynamic.

The increased HE values for the New York spot futures compared to the other regional spot prices indicate that producers in the New York market can better use these models to provide hedging against price fluctuations than producers in the New York and Gulf Coast markets. The ability to use the New York price to conduct higher effectiveness measures may be visible in the lowered volatility within the conditional correlations in the New York spot price and ethanol futures price. The visual inspection of Figure 2 is an additional example of the increased information that can be gathered from using a DCC-GARCH. In this case it allows market participants and researchers a visual guide to addressing the differences in conditional correlations between multiple commodities and a single futures price.

Conclusion

This paper tested two multivariate conditional correlation models for use in the construction of futures hedging portfolios for ethanol futures. The results from this work can be applied by ethanol producers and market participants of related commodities to hedge against price fluctuations in ethanol. Both the CCC-GARCH and the DCC-GARCH proved to be appropriate models for creating ethanol hedging portfolios.

In the case of the results in Table 3.6, the CCC-GARCH has a lowered hedged portfolio variance resulting in a higher hedging effectiveness percentage. These results both Multivariate

GARCH models are displayed to show that they can both be used. However, the confirmed presence of a dynamic component in the DCC-GARCH model makes it a more appropriate model. This confirmation is found in Table 3.5 with the measured significance of the a and b variables from the DCC-GARCH equation (5).

Also interesting and worth additional research is the geographic component of any applied hedging strategy. The hedging effectiveness of each model varies depending on the geographic spot commodity selected. This distinction is an important advance to identify the different geographic patterns of ethanol spot prices in different regions. It would behoove suppliers and purchasers of ethanol in different markets to be aware of the differences in pricing patterns and their behavior compared to ethanol futures to ensure that an appropriate hedging model is considered. This is further notable in the visual inspection of the dynamic conditional correlations, how they change over time and the volatility of these conditional correlations. Additional research on this point is warranted to identify the causes of different price patterns of ethanol in different regions and potential opportunities for arbitrage.

Most importantly, the use of multivariate models in the ethanol future market for the construction of efficient portfolios is a signal that the ethanol market is a viable financial tool for lowering risk for ethanol producers and market participants. This work verifies that the volume and transaction history within the ethanol market is sufficient to facilitate the use of the market as the principal hedging instrument for ethanol producers without having to rely on related futures commodities such as agriculture or energy futures.

Table 1

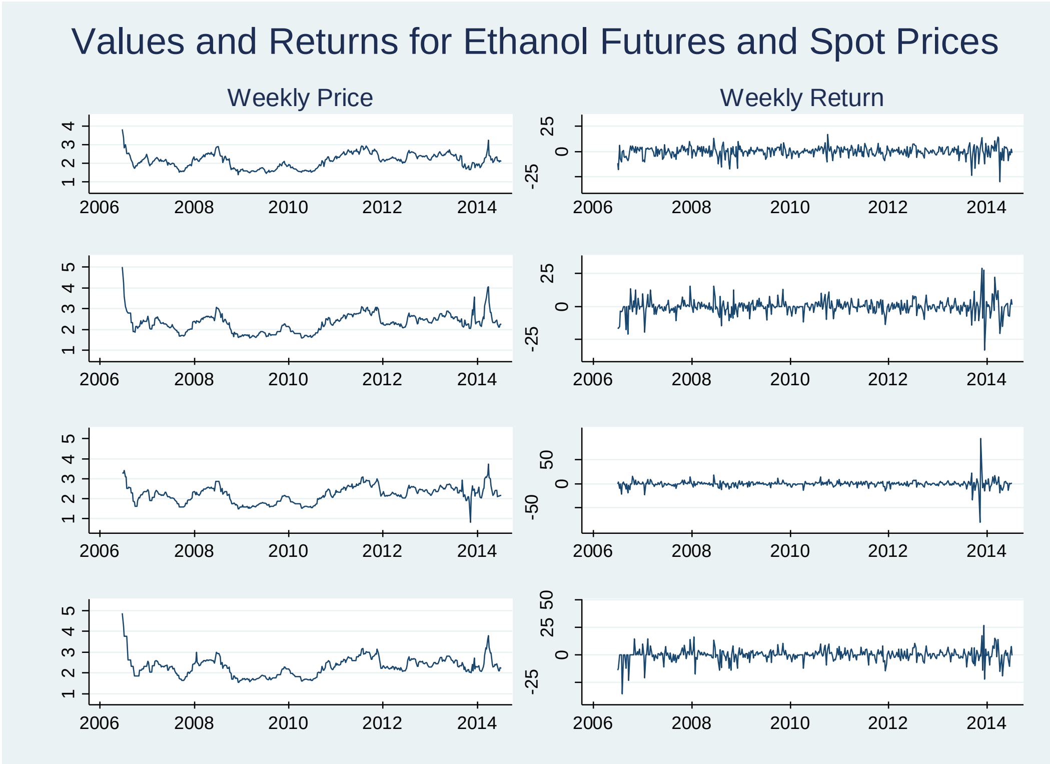
Table 1

Descriptive Statistics

	N	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis	LB(20)
prices								
ethanol futures	420	2.139	0.386	1.398	3.830	0.013	0.724	3184.079***
ethanol spot (NY)	420	2.313	0.447	1.580	5.000	0.000	0.000	2329.710***
ethanol spot (CHI)	420	2.203	0.411	0.820	3.720	0.185	0.856	2703.258***
ethanol spot (GULF)	420	2.306	0.444	1.540	4.880	0.000	0.000	2114.676***
returns								
ethanol futures	419	-0.144	5.198	-30.214	17.031	0.000	0.000	24.300
ethanol spot (NY)	419	-0.190	5.802	-33.085	28.881	0.095	0.000	12.127
ethanol spot (CHI)	419	-0.100	8.243	-79.729	94.039	0.000	0.000	65.51***
ethanol spot (GULF)	419	-0.187	5.674	-35.477	26.714	0.000	0.000	12.255

Note: This table presents the descriptive statistics of the market price and returns for the futures and spot values of ethanol from 2006-2013. This table reports, mean, standard deviation, skewness, kurtosis and the Ljung-Box(LB) for autocorrelation up to (20) lags.
*** p<0.01, ** p<0.05, * p<0.1

Figure 1



Note: Figure 1 displays the weekly prices and returns for ethanol futures and the three ethanol spot prices: New York Harbor, Chicago and Gulf Coast from 2006 through 2014. The graphs display similar trends for the overall time period.

Table 2

Correlation coefficients between ethanol futures and spot prices

	ethanol futures	ethanol spot (ny)	ethanol spot (chi)	ethanol spot (gulf)
ethanol futures	1			
ethanol spot (ny)	0.9095	1		
ethanol spot (chi)	0.9275	0.9425	1	
ethanol spot (gulf)	0.9194	0.9605	0.9407	1

Note: This table displays the correlation between ethanol futures and three U.S. based spot prices for ethanol: New York, Chicago and Gulf.

Table 3

Unit Root Tests

	ADF	DFGLS	Phillips-Peron
Panel A: ethanol prices			
ethanol futures	-3.599***	-1.832	-4.882***
ethanol spot (NY)	-4.491***	-1.803	-6.501***
ethanol spot (CHI)	-4.459***	-2.416	-4.249***
ethanol spot (GULF)	-5.007***	-1.963	-6.178***
Panel B: ethanol returns			
ethanol futures	-9.975***	-7.632***	-19.591***
ethanol spot (NY)	-10.650***	-5.972***	-20.004***
ethanol spot (CHI)	-12.481***	-18.337***	-24.984***
ethanol spot (GULF)	-9.461***	-6.270***	-20.883***

This table reports the Augmented Dickey Fuller (ADF), modified Dickey-Fuller-GLS (DF-GLS) and Phillips-Peron Unit Root Tests for both prices and returns of ethanol spot and futures. *, **, *** indicate the significance level of 10%, 5% and 1%, respectively.

Table 4

CCC Results

returns	mean equation			Variance equation			Persistence		
	y0	y1	y2	ϖ	α	β	α + β	CCC	Log-Likelihood
New York Harbor									
ethanol futures	-0.100	0.089	-0.025	2.577**	0.197***	0.707***	0.904	0.605***	-2380.045
	(0.199)	(0.062)	(0.057)	(1.001)	(0.050)	(0.067)		(0.031)	
ethanol spot (NY)	0.004	0.579***	-0.280***	1.117***	0.112***	0.844***	0.956		
	(0.195)	(0.058)	(0.058)	(0.411)	(0.027)	(0.034)			
Chicago									
ethanol futures	-0.064	0.097*	-0.013	2.947***	0.265***	0.638***	0.903	0.522***	-2462.84
	(0.194)	(0.057)	(0.030)	(1.129)	(0.068)	(0.077)		(0.036)	
ethanol spot (CHI)	0.106	0.602***	-0.334***	6.107***	0.609***	0.398***	1.007		
	(0.200)	(0.049)	(0.058)	(1.493)	(0.113)	(0.077)			
U.S. Gulf									
ethanol futures	-0.155	0.113*	-0.040	2.146**	0.221***	0.708***	0.929	0.480***	-2436.853
	(0.196)	(0.061)	(0.050)	(0.875)	(0.055)	(0.063)		(0.038)	
ethanol spot (GULF)	-0.116	0.568***	-0.242***	1.775**	0.155***	0.784***	0.939		
	(0.200)	(0.059)	(0.058)	(0.718)	(0.051)	(0.061)			

Note: Table 4 reports the results of the CCC-GARCH model for futures and spot prices and reports the constant conditional correlation of each spot in regards to the futures price returns. Mean equation: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

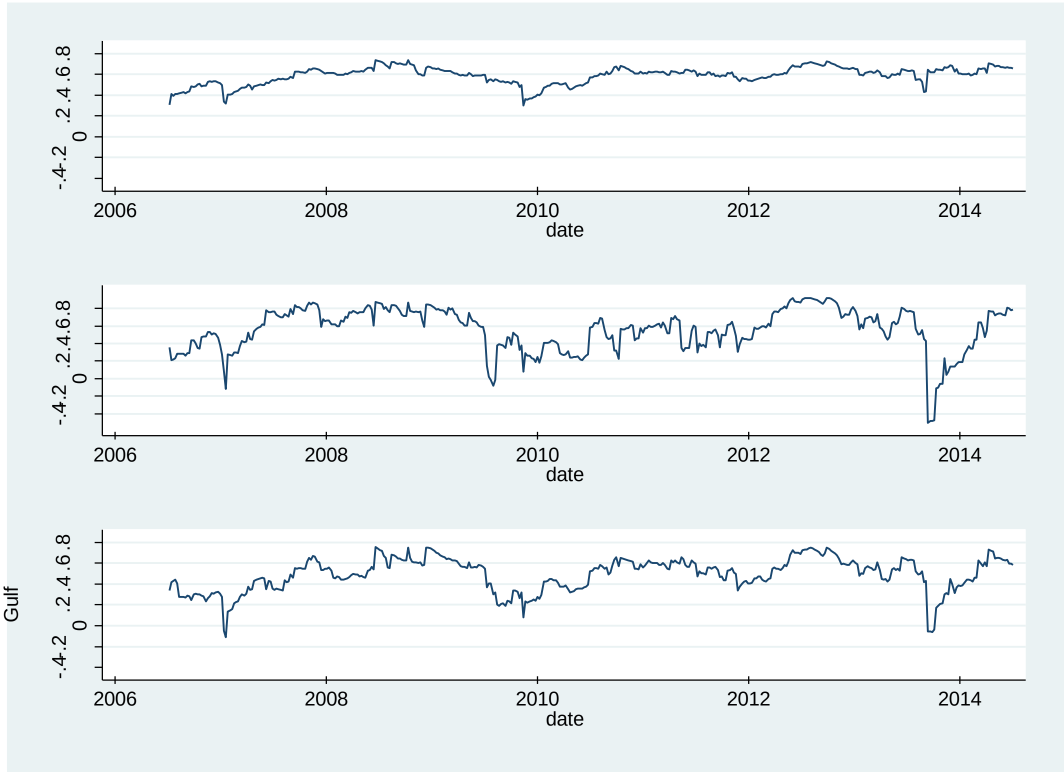
Table 5

DCC Results

returns	mean equation			variance equation			Persistence	DCC Equation		
	γ0	γ1	γ2	ϖ	α	β	α + β	a	b	Log-Likelihood
New York Harbor										
ethanol futures	-0.095	0.096	-0.020	2.209**	0.216***	0.721***	0.937	0.033*	0.915***	-2377.521
	(0.195)	(0.063)	(0.058)	(0.883)	(0.052)	(0.060)		(0.017)	(0.045)	
ethanol spot (NY)	0.016	0.602***	-0.296***	1.169***	0.133***	0.831***	0.964			
	(0.191)	(0.059)	(0.059)	(0.448)	(0.032)	(0.036)				
Chicago										
ethanol futures	-0.078	0.091	-0.007	3.209***	0.351***	0.632***	0.983	0.130***	0.860***	-2435.641
	(0.185)	(0.057)	(0.034)	(1.175)	(0.073)	(0.064)		(0.016)	(0.017)	
ethanol spot (CHI)	0.023	0.598***	-0.333***	4.816***	0.505***	0.519***	1.024			
	(0.185)	(0.051)	(0.054)	(1.250)	(0.108)	(0.076)				
U.S. Gulf										
ethanol futures	-0.140	0.120**	-0.028	2.221**	0.259***	0.699***	0.958	0.072***	0.884***	-2428.425
	(0.190)	(0.059)	(0.050)	(0.905)	(0.059)	(0.061)		(0.025)	(0.052)	
ethanol spot (GULF)	-0.088	0.598***	-0.260***	1.959**	0.184***	0.767***	0.951			
	(0.194)	(0.058)	(0.057)	(0.788)	(0.058)	(0.062)				

Note: Table 5 reports the results of the CCC-GARCH model for futures and spot prices and reports the dynamic conditional correlation of each spot in regards to the futures price returns. Mean equation: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 2 Dynamic Conditional Correlations



Note: Figure 2 displays the Dynamic Conditional Correlations for each of the spot prices when modeled alongside the ethanol futures time series. The existence of dynamic conditional correlation not only displays that the correlation is dynamic but that the dynamics differ for each of the regional spot prices of ethanol.

Table 6
Alternative Hedging Strategies

Model	Optimal portfolio weights	Average OHR	Unhedged Portfolio Variance	Hedged Portfolio Variance	Hedge Effectiveness (%)
CCC-GARCH					
NY	0.536	0.597	33.660	22.820	32.205%
CHI	0.439	0.504	67.945	54.716	19.471%
GULF	0.950	0.507	32.197	25.010	22.321%
DCC-GARCH					
NY	0.546	0.585	33.660	23.294	30.795%
CHI	0.489	0.586	67.945	63.091	7.145%
GULF	0.513	0.501	32.197	26.135	18.827%

Note: Table 3.6 shows the optimal portfolio weights, average optimal hedge ratios, portfolio variance and hedge effectiveness of each model for all ethanol spot returns compared with the ethanol futures returns given the conditional correlation of each model.

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