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Determining the Effectiveness of Exchange Traded Funds as a Risk Management Tool for Southeastern Producers

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Determining the effectiveness of exchange traded funds as a risk management tool for southeastern producers

By

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Determining the effectiveness of exchange traded funds as a risk management tool for southeastern producers

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This thesis investigates the use of commodity exchange traded funds (ETFs) as a price risk management tool for agriculture producers. The effectiveness of ETFs in hedging price risk will be determined by calculating optimal hedge ratios. This thesis will investigate the southeastern producer's ability to hedge their price risk for corn, soybeans, live cattle and diesel fuel. Hedge ratios will be calculated using ordinary least squares (OLS), error correction model (ECM), and generalized autoregressive conditional heteroscedasticity (GARCH) regression models. A utility maximization framework will be used to determine how transaction costs and risk aversion effect the optimal hedge ratio. The main finding is that ETFs provide producers with a reliable tool when hedging their output and input price risk. The presence of transaction costs decrease the effectiveness of an ETF hedge.

DEDICATION

This thesis is dedicated to my family who have provided valuable support throughout my school career.

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CHAPTER I

INTRODUCTION

Over the last few years producers have seen an increase in the volatility of commodity prices. This has caused agribusiness producers and the agricultural industry to face different types of price risk. One reason for this increase in volatility of commodity prices is the overall price increase in commodities (Schweikhardt, 2009). Many price risk management tools have existed for years, including forward contracts, futures contracts, option contracts, and insurance. Even though these instruments are available as a tool to help producers offset their price risk, it has been shown that many do not take advantage of them (Shapiro and Brorsen, 1988). One main reason is the size of the quantity requirements needed for futures and options contracts. These quantity requirements are usually too large for small and mid-sized producers and they are unable to take advantage of using futures or option contract to hedge their price risk.

The Chicago Mercantile Exchange (CME) offers a feeder cattle future contract that has a quantity requirement of 50,000 lbs. Feeder cattle are weaned calves that typically range in weight from 600-800 lbs. To hedge their price risk using futures contracts, a cattle producer would need at least 83 head of feeder cattle weighing 600 lbs. In 2012, 72 percent of Mississippi cattle producers had less than 50 head of cattle (NASS, 2012). A high majority of cattle producers in Mississippi are exposed to fluctuations in cattle prices without any real means of protection. The Agricultural Risk Protection Act of 2000 gave livestock producers the ability to protect either risk or gross margin with insurance through the Risk Management Agency. Livestock risk protection and livestock gross margin protection insurance are available to all producers. USDA data shows that only 0.5 percent of all cattle where protected under the two policies in 2007.

The CME offers a soybean futures contract with a quantity requirement of 5,000 bushels. In 2012, 46 percent of soybean farms had less than 100 acres (NASS, 2012). At the national average yield of 40 bushels an acre that year, a 100 acre farm would produce 4,000 bushels (NASS). This level of production does not allow for small scale soybean producers to hedge their price risk in the futures market. The CBOT also offers a corn futures contract with a quantity requirement of 5,000 bushels. Based off the national average yield of 123 bushels an acre in 2012, in order to hedge their price risk in the futures market, a producer would need to have at least 40 acres of corn in production (NASS, 2012). In 2012, 34 percent of corn farms had less than 50 acres. While there are futures contracts that have a quantity requirement of 1,000 bushels for both corn and soybeans, they face a liquidity problem that make them unreliable for use by producers. These mini contracts trade on the CME but at a much lower volume than the regular contracts. For soybeans they are almost 15 times lower, and for corn they are almost 20 times lower for the nearby contracts. For a producer to know they can effectively hedge their price risk, they need the futures contract to be highly liquid. When a producer decides to lift their hedge, there must be somebody willing to purchase or sell them the necessary futures contracts to do so. A highly liquid futures contract ensures the producer that this will be possible.

There has also been a recent development between the relationship of biofuels and traditional energy products and its effects on the resulting demands on agricultural products, especially corn and soybeans. Government policy, such as the Renewable Fuel Standard (RFS), has been shown to have created strong linkage between agricultural commodity prices and energy prices (Harri, Nalley, and Hudson, 2009). Buguk, Hudson, Hanson (2003) and Harri and Hudson (2009) also have found that there is evidence of volatility spillover from energy markets into agricultural markets. While some risk management tools exist for such inputs as feed ingredients for cattle producers, few risk management tools exist for input products like fuel, fertilizer, propane, and processed feedstuffs.

A heating oil futures contract is offered with a quantity requirement of 1,000 barrels (or 42,000 gallons). This could be used by producers to hedge their input price risk of diesel fuel, but the quantity requirement is impractical for most producers. It takes 35 gallons of diesel fuel to grow one acre of irrigated soybeans (MSU, 2015). A producer would need to grow 1200 acres of soybeans in order to use enough diesel fuel to be able to use one futures contract to hedge their price risk. In 2012, 89 percent of row crop operations in Mississippi had less than 1,000 acres.

Objectives

This research proposes a new risk management tool that can provide small producers with the ability to protect themselves from price risk of their outputs. It also proposes a way for producers to be protected from fluctuations in input price risk. This new tool would be the use of Exchange Traded Funds (ETFs). An ETF is an instrument that resembles a mutual fund, but is priced throughout the trading day. The ETFs we will use are created from a combination of various futures contracts for a commodity. The value of the ETF is determined by the values of all underlying futures contracts. The advantage of an ETF is that they can be traded at much smaller increments than a futures contract. Since they are priced and traded throughout the trading day, they provide liquidity and flexibility to the user. Small and mid-sized producers are also able to take advantage since there are minimal quantity requirements. ETFs are also offered for inputs such as fuel, fertilizer, propane, and feedstuffs. This offers a potential useful tool to help offset input price risk for all producers. This research estimates the effectiveness of ETFs as a viable instrument to use when hedging against price risk and the benefits an ETF hedge can provide to producers. An optimal ETF hedge is determined, where the optimal hedge is the percentage of a producer's total quantity of output or input that should be hedged.

Thesis Overview

The first chapter has provided an introduction to the problems small size producers face when attempting to protect themselves from price risk on their inputs and outputs and presented the objectives of this study. Chapter II will present past research in the areas of minimum variance hedging and the use of ETFs to hedge price risk. Chapter III will discuss the conceptual framework behind a basic naïve hedge. Chapter IV will present the data and various methods that will be used to meet the objectives of this study. Chapter V will present the results of the study and Chapter VI will contain concluding remarks and possible extensions of the work.

CHAPTER II

LITERATURE REVIEW

There have been many studies that investigate the use of the futures market by producers to hedge their price risk. These studies have explored the effectiveness of a direct futures hedge as well as cross hedges. A cross hedge is when a commodity is hedged using the futures of a different commodity. The literature includes studies that have derived optimal hedging ratios and looked at the most efficient econometric models to use when deriving them. An optimal hedge ratio indicates the percentage of a producer's quantity of output or input that should be hedged. Others have examined how risk preferences, production costs, and other decisions producers face influence the optimal hedge ratio. The following section presents literature on general futures hedging, followed by a short section on work that has looked at the use of ETFs to hedge commodity price risk.

Futures Hedging

The body of minimum variance hedging literature is quite extensive. Alexander and Barbosa (2007) look at the effectiveness of various minimum variance hedging techniques and provide an extensive review of the literature. One of the highlights of this overview is Johnson (1960), who was the first to use a minimum variance criterion to calculate a hedge ratio based on a specific cash price. Papers following Johnson (1960) investigated if the minimum variance criterion was appropriate. Howard and D'Antonio

(1984) attempt to maximize the Sharpe ratio to derive the optimal hedge ratio. Cheung, Kwan, and Yip (1990) and Lien and Luo (1993) approach hedging effectiveness by minimizing the mean extended-Gini (MEG) coefficient. The Gini coefficient quantifies risk similar to how variance does and the Gini's mean difference is half the expected value of the distance between all pairs of returns (Shalit and Greenberg, 2013). Lien and Tse (1998, 2000) and Mattos, Garcia, and Nelson (2008) used the objective of minimizing the generalized semivariance. Semivariance is a measure of the dispersion of all observations that fall below the mean of a data set.

Cecchetti, Cumby, and Figlewski (1990) found the optimal hedge ratio of treasury bills by maximizing an expected utility function. An autoregressive conditional heteroscedasticity model was used to calculate the conditional variance and covariance matrix, and then the objective function was maximized with respect to the hedge ratio.

Lapan and Moschini (1994) calculated optimal hedge ratios for Iowa soybeans taking into account price, basis, and production risk. When a producer places a hedge, the purpose is to trade their price risk for basis risk. The basis is the difference between the cash and futures price. Basis risk is the uncertainty about basis at the time the hedge is lifted. The authors developed a hedging model where a producer faces these risks and assumed a constant absolute risk aversion (CARA) utility function. They found that the optimal futures hedge was sensitive to risk attitudes.

Chen, Lee, and Shrestha (2003) did a comprehensive review of literature concerning hedge ratios. They compiled a review of articles that had developed both theoretical and empirical models for hedge ratios. This paper is an excellent reference on how the techniques of estimating hedge ratios have developed over time.

Ederington (1979) empirically calculated minimum variance hedge ratios using ordinary least squares (OLS) regression methods. The paper calculated hedge ratios for Government National Mortgage Association futures, wheat, corn, and T-bill futures using weekly data. It was found that as the length of the hedging period increased, the hedge ratio increase.

Baillie and Myers (1991) derived the minimum variance hedge ratios for beef, coffee, corn, cotton, gold, and soybeans using a bivariate GARCH model. Their model allowed for time-varying estimations of the conditional covariance matrix and thus time-varying hedge ratios to be derived. The authors found that the assumption of constant optimal hedge ratios was inappropriate.

Kroner and Sultan (1993) proposed using a bivariate generalized autoregressive conditional heterosedasticity error correction model to derive the minimum variance hedge ratio. The error correction term allowed for the long run relationship between the cash and futures price to be included in the model. The GARCH parameters allowed for new information over time to influence the hedge ratio and for time varying hedge ratios to be derived. Garbade and Silber (1983), Myers and Thompson (1989), and Ghosh (1993) take into account the existence cointegration between the cash and futures price series also. Conversely, Lien (2004) has shown that the omission of an error correction term will not have a significant effect on hedging effectiveness.

Moschini and Myers (2002) found significant GARCH effects in both the corn, cash and futures markets. They concluded that the optimal hedge ratios for the weekly storage hedging of corn to be time-varying.

Lence (1995) investigated the difference between optimal hedge ratios of a risk minimizing approach and the utility maximizing approach. It was found that the hedge ratios deviate from each other. Interest rates and transaction costs were found to be factors that influenced this deviation. Lence (1996) expanded the study to include stochastic production and found that brokerage fees were important in causing the deviation between the two types of hedge ratios.

Dhuyvetter, Albright, and Parcell (2001) researched forecasting and hedging input prices. The researchers estimated the ability to hedge diesel fuel, anhydrous ammonia, and natural gas using futures contracts. They found that diesel fuel could be cross hedged using a crude oil or heating oil futures. They also mentioned that these contracts may be too large for individual producers to use effectively.

ETF Hedging

In academic literature there are not many studies that have examined the ability of ETFs to track specific cash prices of the commodities in which they are designed to follow. Murdoch and Richie (2008) looked at the ability of the United States Oil Fund (USOF) to be used as a hedging instrument. They looked at the relationship of the price of the USOF ETF and the price of the West Texas Intermediate (WTI) oil futures and spot price. To investigate the use of the USOF ETF as a hedging instrument, the authors performed a correlation analysis of the USOF with the spot and futures price. Based on the estimated correlations the USOF appears to be a useful hedging tool for investors. The authors further looked at the degree in which the USOF price deviates from the futures market it is supposed to replicate. They found that the futures-USOF basis is significantly more volatile than the futures-spot basis. This led the authors to conclude that “although the fund prices and price changes are reasonably correlated with oil markets, an investor faces more uncertainty with the USOF and may or may not be able to sustain an effective hedge against volatile oil prices” (Murdoch and Richie 2008, p. 341). They also found that the futures-USOF basis is greater during periods of contango, which is when futures prices are greater than cash prices. This can play an important role in the effectiveness of the hedge.

Plamondon and Luft (2012) built upon the work of Murdoch and Richie (2008), and compared the returns of physical and derivative commodity ETFs to the returns of their underlying spot commodity returns. ETFs were split into two groups, those that held the physical commodity and those that used futures to derive the ETFs value. They regressed the returns of the spot price on the returns of the corresponding ETF.The authors found that for both ETF groups, there was no statistical difference between the ETF returns and the spot commodity returns.

CHAPTER III

CONCEPTUAL FRAMEWORK

The following chapter describes the intuition behind optimal hedge ratios. As seen in Chapter II, the different ways to calculate optimal hedge ratios has been researched and improved upon since the inception of hedging theory. The following framework shows how the optimal hedge ratio is derived using the minimum variance and mean-variance approaches. It is then shown how under certain assumptions the minimum-variance and mean-variance approaches return the same optimal hedge ratio. It is further shown how the optimal hedge ratio can be time-varying.

Deriving Optimal Hedge Ratios

The most basic hedging strategy is a naïve hedge. With this strategy a producer with a position in the cash market would take an opposite position in the futures market. A producer of a commodity during the production period is considered a buyer of the commodity. Therefore, to hedge against price risk the producer needs to sell futures contracts. When the producer sells a unit of goods in the cash market, they would then buy back the futures contracts. The producer would then have been perfectly hedged as long as both the cash and futures prices changed by the same amount.

Combining the work of Working (1953) with the naïve hedging strategy, Johnson (1960) and Stein (1961) applied basic portfolio theory and incorporated expected profit maximization with the risk avoidance ability of traditional hedging to derive the optimal hedging position, or hedge ratio. The optimal hedge ratio in this framework is the variance minimizing ratio.

Following the work of Ederington (1979) the minimum variance hedge ratio is derived as follows. The expected returns on a hedge position are specified as follows:

$$E(R) = X_c E\left[P_c^2 - P_c^1\right] + X_f E\left[P_f^2 - P_f^1\right] - K\left(X_f\right) \tag{3.1}$$

and the variance of returns is

$$Var(R) = X_c^2\sigma_c^2 + X_f^2\sigma_f^2 + X_c X_f \sigma_{cf}\ , \tag{3.2}$$

where X_c and X_f are cash and futures market holdings, P_c^1 and P_c^2 are the cash prices for time periods t_1 and t_2 respectively, P_f^1 and P_f^2 are the futures prices for time periods t_1 and t_2 respectively, $K(X_f)$ is the transaction costs of implementing a hedge, and σ_c, σ_f, and σ_{cf}, represent the variance of the cash price, variance of the futures price, and the covariance of the cash and futures prices respectively.

When letting $b=-X_f / X_s$ represent the portion of the spot positioned that is hedged, then (3.2) becomes

$$Var(R) = X_c^2(\sigma_c^2 + b^2\sigma_f^2 - 2b\sigma_{cf}) \tag{3.3}$$

and (3.1) becomes

$$E(R) = X_C\left\{(1-b)E(P_c^2 - P_c^1) + b(E(P_c^2 - P_c^1) - bE(P_f^2 - P_f^1)\right\} - K(X_c, b)\,. \tag{3.4}$$

If $E(\Delta B) = E\{P_f^2 - P_c^2 - (P_f^1 - P_c^1)\}$, which represents the expected change in the basis, then equation (3.4) can be written as

$$E(R) = X_c[(1-b)E(P_c^2 - P_c^1) - bE(\Delta B)] - \mathrm{K}(\mathrm{X}_c, b)\,. \tag{3.5}$$

It can be seen from this equation that if the expected basis is zero, then as $b \rightarrow 1$ the expected gains or losses are minimized.

To find b that minimizes risk, take the partial derivative of (3.3) with respect to *b,*

$$\frac{\partial Var(R)}{\partial b} = X_c^2 \left\{ 2b\sigma_f^2 - 2\sigma_{cf} \right\}. \tag{3.6}$$

Setting (3.6) equal to zero one obtains

$$b^* = \frac{\sigma_{cf}}{\sigma_f^2}. \tag{3.7}$$

A criticism of the mean-variance approach to hedging is that it ignores the expected returns of the hedged position. To account for this a mean-variance approach was created that accounts for both the expected returns and the variance.

Following the work of Kroner and Sultan (1993), the mean-variance hedging strategy can be derived as follows. The returns to a producer who has a hedged position are

$$R = \Delta C - b\Delta F, \tag{3.8}$$

where R is the returns, ΔC is the change in cash price, and ΔF is the change in futures prices. It is then assumed that the producer faces a mean-variance expected utility function

$$EU(R) = E(\mathrm{R}) - \gamma \,\mathrm{var}(\mathrm{R}), \tag{3.9}$$

where γ is the degree of risk aversion $(\gamma > 0)$.

Using the objective function for the variance of returns as proposed by Johnson (1960) the optimal hedge ratio is solved using

$$\max_b EU(R) = \max_b \left\{ E(\Delta C) + \mathrm{b}\mathrm{E}(\Delta\,\mathrm{F}) - \gamma \left[\sigma_{\Delta C}^2 + b^2\sigma_{\Delta F}^2 - 2b\sigma_{\Delta C\Delta F} \right] \right\}, \tag{3.10}$$

where $\sigma^2_{\Delta C}$ is the variance of change in cash prices, $\sigma^2_{\Delta F}$ is the variance of change in futures prices, and $\sigma_{\Delta C \Delta F}$ is the covariance between changes in cash and changes in futures prices.

The equation is solved for b, which gives the optimal hedging ratio as

$$b^* = \frac{E(F) + 2\gamma\sigma_{\Delta C \Delta F}}{2\gamma\sigma^2_{\Delta F}}. \tag{3.11}$$

If futures prices follow a martingale (i.e. the expected returns on the futures contracts is zero), then the optimal hedge ratio can be written as

$$b^* = \frac{\sigma_{\Delta C \Delta F}}{\sigma^2_{\Delta F}}. \tag{3.12}$$

Notice that this is the same as the minimum variance optimal hedge ratio.

The hedge ratio in (3.7) or (3.12) assumes that the distribution of cash and futures prices is constant over time. Kroner and Sultan (1993) showed that the hedge ratio could be expressed as time-varying by specifying the returns equation as

$$R_t = \Delta C_t - b_{t'} \Delta F_t, \tag{3.13}$$

where $t' > t$. The producer now calculates the optimal hedging position by maximizing the expected utility function

$$E_t U(R_{t+1}) = E_t(R_{t+1}) - \gamma\sigma^2_t(R_{t+1}), \tag{3.14}$$

where risk is now measured by conditional variances, and it is shown that the expectation and variance operators are conditioned on information available at time *t*. The utility maximizing hedge ratio at time *t* assuming that futures prices are a martingale is

$$b_t^* = \frac{\sigma_t(\Delta C_{t+1}, \Delta \mathrm{F}_{t+1})}{\sigma_t^2(\Delta \mathrm{F}_{t+1})}. \tag{3.15}$$

The optimal hedge ratio is similar to the conventional hedge ratio, but the variance, covariance and the hedge ratio are now time-varying conditioned.

CHAPTER IV

DATA AND METHODS

In Chapter III, the concept of an optimal hedging ratio was derived and shown to be the ratio of the covariance of cash and futures prices and the variance of the futures price. This same concept can be extended to place an ETF hedge. The optimal hedge ratio when using ETFs will be the ratio of the covariance of cash and ETF prices and the variance of the ETF price. The following sections will present the data used in this study and the methods used to determine optimal hedge ratios for futures and ETFs. The four commodities examined in this study are corn, soybeans, live cattle, and diesel fuel. Time series data were checked for stationarity and for cointegration. This study calculated hedge ratios using an ordinary least squares (OLS), error correction model (ECM), and a generalized autoregressive conditional heteroscedasticity (GARCH) model. Historical data was used to simulate cash, futures, and ETF price changes to investigate how transaction costs and a producer's risk aversion affect the optimal hedge ratio.

Data

The data for this study consist of weekly historical cash and futures prices of corn, soybeans, live cattle, and on the input side, diesel fuel. The weekly historical closing price of the relevant ETFs were used for each commodity. Corn and soybean cash prices are the local prices from Greenville, Mississippi. Live cattle prices are an average for

1,000 to 1,300 pound cattle in Texas and Oklahoma. Diesel prices were obtained from the U.S. Energy Information Administration for the Gulf Coast region.

The ETF used for corn will be the Teucrium Corn Fund (NYSE: CORN) created June 9, 2010. The time period for corn used in this research will therefore be June 2010 to July 2015. Since ETFs are designed similar to a mutual fund, they are priced based on the fund's Net Asset Value (NAV). The NAV is the net assets of the fund divided by the outstanding shares. The value of the CORN ETF's assets are made up of three CBOT futures contracts. These futures contracts are the second to-expire-contract from the current date with a weight of 35 percent, the third-to-expire contract from the current date with a weight of 30 percent and the contract expiring in the December following the third-to-expire contract with a weight of 35 percent.

The ETF used for soybeans will be the Teucrium Soybean Fund (NYSE: SOYB) created September 16, 2011. The time period for soybeans used in this research will be September 2011 to July 2015. The SOYB ETF's assets are made up of three CBOT soybean futures contracts. These three CBOT futures are the second to-expire-contract from the current date weighted 35 percent, the third-to-expire contract from the current date weighted at 30 percent and the contract expiring in the November following the third-to-expire contract weighted 35 percent. The CBOT soybean contracts for August and September are not included in the fund due to the less liquid markets for these contracts.

To hedge diesel fuel this study will be using a heating oil ETF, United States Diesel-Heating Oil Fund LP (NYSE: UHN). This fund was created April 9th, 2008. The time period of April 2008 to August 2015 will be used for diesel fuel. UHN is designed to mimic the daily changes of heating oil (No. 2 Fuel) for delivery at the New York harbor, as measured by the daily changes in the NYMEX heating oil (No. 2 Fuel) futures contract. The UHN uses the near month contract, and begins to roll them over when they are within two weeks of expiration. The fund also may invest in forward and swap contracts.

For live cattle an Exchange Traded Note (ETN) will be used instead of an Exchange Traded Fund (ETF). The difference between the two is that ETNs fall under the governance of the Securities ACT of 1933, while ETFs falls under the governance of the Investment Company Act of 1940. ETNs may be managed like a fund and traded like ETFs, but they do not report the same way and are governed under slightly different rules (Ferri, 2009). For live cattle the iPath Bloomberg Subindex Total Return ETN (NYSE: COW) will be used. This note was created on October 23, 2007. This study will therefore look at the price series from October 2007 to May 2015 for live cattle. COW's index is a combination of 54 percent live cattle and 46 percent lean hogs futures contracts. Due to this funds designation as an ETN, the exact futures contracts used to determine the value do not have to be reported.

Unit Root and Cointegration Testing

When dealing with time series data, it must be checked that the series follows a stationary stochastic process. Time series data is stationary when the mean and variance are constant over time. All price series data used in this research are checked for the presence of a unit root. Using the random walk model of a nonstationary time series Y, the equation can be specified as:

$$Y_t = \rho Y_{t-1} + u_t\,, \tag{4.1}$$

where $-1 \le \rho \le 1$. If ρ=1, then the time series follows a random walk and is nonstationary. This case is referred to as a unit root problem. If $|\rho| < 1$, then the price series is said to be stationary.

A Dickey-Fuller (DF) test will be used to check for the presence of a unit root in the futures, ETF, and cash logged prices for all commodities. A log normal distribution is assumed as in Hull (2006). Equation (4.1) cannot be tested for the hypothesis ρ=1 using a *t*-test because the *t*-test is biased in case of a unit root. Therefore, equation (4.1) must be manipulated by subtracting Y_{t-1} from both sides to obtain

$$\Delta Y_t = \delta Y_{t-1} + u_t\,, \tag{4.2}$$

where $\delta = (\rho\text{-}1)$ and Δ is the first difference operator.

Equation (4.2) is estimated and the null hypothesis of $\delta = 0$ is tested. If δ=0, then ρ=1. If the null hypothesis is not rejected, then a unit root is present and the time series is nonstationary. When estimating equation (4.2), it is shown that the estimated *t*-value of the coefficient does not follow the t-distribution, so instead Dickey and Fuller calculated the *tau* and *rho* statistics which are used to conduct the hypothesis test.

To understand cointegration between price series, consider the vector autoregression model

$$\Delta X_t = \prod X_{t-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \varepsilon_t\,, \tag{4.3}$$

where $\boldsymbol{X}$ is a vector of cash and futures prices for a commodity, Γ_1 through Γ_{k-1} (2 x 2) and **Π (2 x 2)** are parameters to be estimated. These parameters are estimated for *b* =1, 2.

The definition of cointegration given by Engle and Granger (1987) is the components of the vector $\boldsymbol{X_t}$ are said to be cointegrated of order d, b, denoted $X_t \sim CI(d,b)$, if all components of X_t are $I(d)$ and there exists a vector $\alpha(\neq 0)$ so that $z_t = \alpha' X_t \sim I(d-b)$, $b>0$. The cointegrating vector is α.

In the case of d =1, b = 1, if the variables are cointegrated, then the components of Xt would be integrated to order one, I(1) and zt would be I(0). This shows that the zt will not drift very far from zero if it has a mean of zero. This is the intuition behind the Engle-Granger cointegration test.

The presence of cointegration between the price series will be checked using the two step Engle-Granger approach. Cointegration is present when there is a long run relationship between two price series, which in this study are the cash and futures price series or the cash and ETF price series. As an example of the Engle-Granger test, the first step is to estimate the equation

$$Cash = \alpha_1 + \alpha_2 Fut + u_t, \tag{4.4}$$

where *Cash* is the log cash price, and *Fut* is the log futures price. A Dickey-Fuller unit root test is then performed on the residuals. If the residuals are found to be stationary then the two price series are cointegrated.

Regression Methods

This study will use three different regression techniques to derive optimal ETF hedge ratios, as well as optimal futures hedge ratios for comparison purposes. The three regressions will be an ordinary least squares, error-correction model, and a bivariate generalized autoregressive heteroscedasticity model with an error correction term.

In the following notation, future and ETF prices are interchangeable. Elam and Davis (1990) employed OLS regression to investigate the optimal hedge ratios for feeder cattle. OLS regression sets the dependent variable as the change in cash price and regresses it against the change in futures price.

The resulting regression equation is:

$$\Delta Cash_t = \alpha + \beta \Delta Fut_t = e_t \tag{4.3}$$

where $\Delta Cash_t = Cash_t - Cash_{t-1}$, which is the change in the cash price during the hedging period, and similarly $\Delta Fut_t = Fut_t - Fut_{t-1}$, which is the change in the futures price during the hedging period. The parameter β is a slope coefficient and represents the optimal hedge ratio.

Cash and futures prices may also be cointegrated. A no arbitrage condition means that between futures and cash markets in the long run, the two price series cannot drift far apart. In the short run though, there might be some effect that causes the local cash price to deviate from the futures market price. When this occurs, the OLS regression is biased because of an omitted variable problem. The omitted variable is the long run relationship between the two price series. To address the problem of cointegration an error correction model was developed by Engle and Granger (1987). This model is:

$$\Delta Cash_t = \gamma u_{t-1} + \beta \Delta Fut_t + \sum_{i=1}^{p} \delta_i \Delta Cash_{t-i} + \sum_{j=1}^{q} \phi_j \Delta Fut_{t-j} + v_t \, , \tag{4.4}$$

where $u_{t-1}=Cash_{t-1}-(\alpha+\alpha_1 Fut_{t-1})$ is the error correction term. This term accounts for the long term relationship between cash and futures prices and the lagged variables in the model account for the short term influences. β is again the optimal hedging ratio. The appropriate number of lags will be determined using a minimum information criterion based on the corrected Akaike information criterion. Depending on the results from the two step Engle-Granger cointegration test, either the OLS or the ECM model will be used.

Along with OLS and ECM hedging ratios, we will obtain time varying hedge ratios. This was done by estimating hedge ratios that are conditional on past information, I_{t-1}.

$$\beta_{t-1} = \frac{\operatorname{cov}\left(\Delta Fut_t, \Delta \mathrm{Cash}_t \middle| I_{t-1}\right)}{\operatorname{var}\left(\Delta Fut_t \middle| \mathrm{I}_{t-1}\right)}. \tag{4.5}$$

Since β_{t-1} is conditional on I_{t-1}, the optimal hedging ratio is time varying. To estimate the time varying hedging ratios, a bivariate generalized autoregressive conditional heteroskedasticity (BGARCH) with an error correction model will be used. The conditional mean will be specified as

$$R_t = A + \prod u_{t-1} + \sum_{i=1}^{p} \Gamma_i R_{t-i} + \varepsilon_t \,, \tag{4.6}$$

where $R_t = \begin{bmatrix} \Delta Cash_t \\ \Delta Fut_t \end{bmatrix}$, and the conditional variance will be specified as

$$h_{ii,t} = \omega_i + \eta_i h_{ii,t-1} + \varphi_i \varepsilon_{i,t-1}^2 \,, \tag{4.7}$$

for $i = 1(Cash),\ 2(Fut)$.

The BGARCH model will be estimated using the constant conditional correlation (CCC) specification for the covariance matrix of ε_t. The conditional time-varying optimal hedge ratios are calculated as

$$B_{t-1,t} = \frac{\hat{h}_{12,t}}{\hat{h}_{22,t}} = \frac{\hat{h}_{Cash\,Fut,t}}{\hat{h}_{Fut,t}}. \tag{4.8}$$

This will give us the optimal hedge ratio to use at the time the hedge is placed.

Statistical significant difference between the futures and ETFs optimal hedge ratio for a given model is tested using the following equation

$$t = \frac{\hat{\beta}_{Fut} - \hat{\beta}_{ETF}}{se_{\beta Fut}}, \tag{4.9}$$

where $\hat{\beta}_{Fut}$ is the optimal hedge ratio for futures, $\hat{\beta}_{ETF}$ is the optimal hedge ratio for ETFs, and $se_{\beta Fut}$ is the standard error of $\hat{\beta}_{ETF}$. The null hypothesis for the test is that $\hat{\beta}_{Fut} = \hat{\beta}_{ETF}$. Failing to reject the null hypothesis means that there is no statistical difference between the optimal hedge ratios for futures and ETFs. This test will be conducted on the optimal hedge ratios for the OLS and ECM models for each commodity.

Simulation Methods

The optimal hedge ratio can also be affected by the risk preferences of the producer and the transaction costs of implementing the hedge. An expected utility framework will be used to obtain the certainty equivalents for both futures and ETF hedged and unhedged positions and compare them to determine the effectiveness of ETFs. A similar approach has been used by Collins (1997), Arias, Brorsen, and Harri (2000), and Harri, Riley, Anderson, and Coble (2009).

The producer is assumed to maximize their expected utility according to a von Neumann-Morgenstern utility function. This function is defined over end-period wealth (W_L) and is strictly increasing, concave, and twice continuously differentiable.

Ending wealth will be designated for both short and long hedges. For a short hedge, for an output, ending wealth will be specified as

$$W_L = W_0 + P_L Q_T - C + Q_F (f_0 - f_1 - tc), \tag{4.10}$$

where W_L is the end of period wealth, W_0 is producer's initial wealth, P_L is the price received for the output commodity being hedged, Q_T is the total quantity produced of the commodity, C represents the production cost, Q_F is the quantity of commodity being hedged, f_0 and f_1 are the initial futures price and the price of the futures contract at the time the hedge is lifted, and tc is the transaction cost of placing the hedge. This formula will be used when hedging outputs.

For a long hedge, for an input, ending wealth will be specified as

$$W_L = W_0 + R - C - P_L Q_F + Q_F (f_1 - f_0 - tc) \tag{4.11}$$

where R is revenue of the farm, Q_F is now the quantity of input being hedged, and P_L is the price of the input. The other terms are as previously defined.

A utility maximizing producer has the choice of how much of the commodity (using the output case) to hedge and the objective function becomes

$$\underset{h}{Max} EU = W_0 + P_L Q_T - C + hQ_t (f_0 - f_1 - tc) \tag{4.12}$$

where h is the hedge ratio, and thus hQt is the optimal quantity of commodity to hedge.

Both futures and ETF hedges are estimated for comparison using simulations for corn, soybeans, and diesel fuel. In order to have a long enough series of ETF prices and more observations, past ETF prices are generated using known historical futures prices and known ETF-futures price relationships. Simulated random variables consist of futures price changes, ETF price changes and ending basis. A total of 50,000 futures price changes, ETF price changes and ending basis are simulated. They are simulated from a multivariate normal distribution using a Cholesky decomposition of the covariance matrix for the futures price changes, ETF price changes, and ending basis. Historical futures, ETF, and cash prices are used to estimate the vector of the means and the covariance matrix used in simulations. The means of futures and ETF price changes are set to zero to ensure unbiased futures and ETF prices. The simulated futures price changes, ETF price changes, and ending basis are used to create 50,000 futures, ETF, and cash prices by assuming starting futures and ETF prices for each commodity.

Ending wealth was calculated using either equation (4.10) or (4.11), depending on if a short or long hedge was being implemented. For each commodity the parameters of equations were specified based on the type of producers modeled. Once ending wealth was simulated it was converted to utility values using a constant relative risk aversion (CRRA) utility function, which was specified as

$$E(U)_r = \sum_{i=1}^{n} \frac{1}{n} \frac{W_i^{1-r}}{1-r}, \qquad r \neq 1 \tag{4.13}$$

or

$$E(U)_r = \sum_{i=1}^{n} \frac{1}{n} \ln(W_i), \qquad r = 1 \tag{4.14}$$

where W_i is the ending wealth for repetition i, r is a risk aversion coefficient, and n is the total number of repetitions. For this study, the risk aversion coefficient was r =2, which represents a moderately risk averse producer.

For each level of utility and the given risk coefficient, it is possible to solve Equation (4.13) and (4.14) and obtain a certainty equivalent (*CE*). The *CE* represents the highest sure payment a producer would be willing to pay in order to avoid a risky behavior. The equations for calculating the *CE* for the CRRA utility functions are:

$$CE_r = \left[\overline{U}\left(1-r\right)\right]^{\left(\frac{1}{1-r}\right)} - W_0, \qquad r \neq 1 \tag{4.15}$$

or

$$CE_r = e^{\overline{U}} - W_0, \quad r = 1 \tag{4.16}$$

where $\bar{U}$ is the utility calculated in Equations (4.13) and (4.14).

A higher certainty equivalent is preferred to a lower one. When given two alternative certainty equivalents CE_i and CE_j, if $CE_i > CE_j$ then i is preferred to j. The optimal hedge ratio for each commodity is the hedge ratio that returns the highest certainty equivalent.

Diesel

The hedging period simulated for diesel is March 31st to July 31st. This represents the time period a producer will use the most fuel for planting and irrigating. The United States Diesel-Heating Oil Fund ETF's value is determined by the nearby futures contract. At March 31st, the nearby futures contract is the April contract. The April futures price for the last five days of March were taken and averaged to determine the ETF price. An average of the last five days was used because the corresponding cash prices are weekly. The same process was used to determine the ETF price for July 31st. The August contract is the nearby, and the August futures price for the last five days of July was taken and averaged to determine the ETF price for July 31st. This was done for each year from 2000 to 2015.

Diesel is often an input of production, so a producer would place a long hedge and ending wealth will be determined using equation (4.11). The base farm for this simulation is a 100 acre irrigated soybean farm, with expected production of 60 bushels an acre, and expected cash price of \$9.00 per bushel. Initial wealth is set at \$10,000 and fixed costs of \$475 an acre according to Mississippi State Extension Budgets. Also according to Mississippi State Extension Budgets, this size farm would use about 35 gallons of diesel fuel per acre, both for tractors and irrigation equipment. In Equation (4.11), Q_F is set at 3,500 gallons. Futures and ETF trading costs were determined by averaging various brokerage firms trading fees. Futures trading cost is \$0.0012/gallon. The trading cost for ETFs is \$0.0006 per share.

Placing an ETF hedge comes with additional costs not present when placing a futures hedge. Since an ETF is built similar to a mutual fund, a management fee will be charged to the holder of the ETFs, which is the expense ratio. The United States Diesel-Heating Oil Fund has an annual expense ratio of 0.60 percent. If an individual held ETFs in this fund worth a \$1,000, they would owe \$60 for fund management each year. Since our producer will hold the ETFs for 3 months, he will face an expense ratio of 0.15 percent.

Another added expense of an ETF hedge is the interest on borrowed money. When purchasing ETFs, a buyer must pay 50 percent of the ETFs value. This can present a cash flow issue to the producers, which will result in the need to borrow money in order to place the hedge. The interest rate on borrowing is assumed to be an annual rate of 6 percent. The fund will be held for three months so the interest rate is set at 1.5 percent. Therefore the transaction cost for an ETF is

$$tc_{ETF} = c + (0.5 \times P_e \times \mathrm{I} \times \mathrm{E}) \tag{4.17}$$

where c is the brokerage fee, P_e is the ETF price, I is the interest rate, and E is the expense ratio.

Corn

The hedging period for corn is set at April 31st to October 31st. Since corn is an output, the producer would place a short hedge and thus ending wealth will be simulated using equation (4.10). ETF prices are generated following the combination of futures contracts used by the Teucrium Corn Fund. The ETF price that a producer would face when placing a hedge on April 31st is generated by taking the average of the last five days of April futures prices for the July, September, and December contracts. The July price is then weighted 35 percent, the September price weighted 30 percent, and the December price is weighted 35 percent. These weighted prices are added together to obtain the ETF start price. The ETF price for October 31st, when the producer will lift the hedge, is generated with the same process using the March, May, and December of the next year futures contracts.

Farm size is set at 25 acres and corn production of 175 bushels an acre. In Mississippi 23 percent of farms that harvested corn have 25 or less acres and the Mississippi average for corn production in 2015 was 175 bushels an acre. Total cost of corn production is set at $500 per acre according to 2016 Mississippi State Extension crop budgets and initial wealth at $20,000. The beginning futures price for the simulation was set at $3.87 and the beginning ETF price was set at $3.96. The trading cost for futures is set at $0.03/bu. The trading cost for ETFs is again set at $0.015 a share. The expenses ratio for the Teucrium Corn fund is 2.92 percent and the interest rate is set at an annual rate of 6 percent.

Soybeans

The hedging period for soybeans is set for April 31st to October 31st. The ETF prices are generated following the combination of futures contracts that the Teucrium Soybean Fund uses to determine its value. The process to generate these prices was the same as generating the corn ETF prices. Unlike the corn ETF that uses all futures months, the soybean ETF does not use the futures contracts for August and September due to low trading volume.

The simulation of ending wealth using Equation (4.10) assumes a 100 acre soybean farm producing 60 bushels an acre. A 100 acres of soybeans is the size at which a producer would be on the verge of not being able to use futures to hedge their price risk. Initial wealth is set at $40,000 and fixed costs are set according to 2016 Mississippi State Extension crop budgets at $475 an acre. The trading cost of futures is $0.03/bu. and the trading cost of an ETF is $0.015 a share. The expenses ratio for the Teucrium Soybean Fund is 3.49 percent and the interest rate on a loan is set at an annual rate of 6 percent.

CHAPTER V

RESULTS

The following sections contain the results generated using the methods outlined in the previous chapter. The first section presents some basic summary statistics on the data followed by a section that presents the results of unit root and cointegration tests. The following sections present the hedging results using the regression methods and the simulation methods respectively.

Summary Statistics

Summary statistics for the levels and log-levels of the cash, futures, and ETF prices for each commodity can be found in Tables 5.1- 5.4. A normally distributed variable will have a skewness and kurtosis value of three. The kurtosis measures reported in tables 5.1-5.4 actually measure excess kurtosis, the difference between the observed kurtosis and the kurtosis value for the normal distribution, three. For corn, the distributions of the cash, futures, and ETF prices levels and logs have a low negative skewness. The kurtosis value is negative for these price distributions and indicates the presence of thinner tails of the distribution as compared to the normal distribution. The same is true for the shape of the distribution for soybeans cash, futures, and ETF level and log prices. The live cattle ETF level price exhibits positive skewness and positive excess kurtosis, implying thicker tails than the normal distribution. The distribution of the log live cattle ETF price does not exhibit the excess positive kurtosis but positive skewness is still present. The diesel ETF also has a positive skewness and positive excess kurtosis, but the log price does not.

Table 5.1 Summary Statistics of Corn Cash, Futures, and ETF prices (Levels and Log-Prices)

Variable	**Mean (s.d.)**	**Min**	**Max**	**# of obs**	**Skewness**	**Kurtosis**
Cash Price	5.61(1.35)	3.06	7.83	263	-0.099	-1.412
Futures Price	5.58(1.45)	3.21	8.30	263	-0.026	-1.442
ETF Price	36.41(8.01)	22.63	52.50	263	-0.056	-1.148
Log Cash Price	1.69(0.25)	1.12	2.06	263	-0.326	-1.263
Log Futures Price	1.68(0.27)	1.17	2.12	263	-0.245	-1.414
Log ETF Price	3.57(0.23)	3.12	3.96	263	-0.333	-1.109

Notes: Cash Price - Greenville, Mississippi, ETF- Teucrium Corn Fund.

Table 5.2 Summary Statistics of Soybeans Cash, Futures, and ETF prices (Levels and Log-Prices)

Variable	**Mean (s.d.)**	**Min**	**Max**	**# of obs**	**Skewness**	**Kurtosis**
Cash Price	13.24(2.09)	9.13	17.53	197	-0.209	-0.984
Futures Price	13.05(2.12)	9.17	17.63	197	-0.195	-0.832
ETF Price	23.01(2.16)	18.51	28.53	197	-0.004	-0.436
Log Cash Price	2.57(0.16)	2.21	2.86	197	-0.429	-0.971
Log Futures Price	2.55(0.17)	2.21	2.87	197	-0.450	-0.865
Log ETF Price	3.13(0.09)	2.92	3.35	197	-0.213	-0.523

Notes: Cash Price - Greenville, Mississippi, ETF- Teucrium Soybean Fund.

Table 5.3 Summary Statistics of Live Cattle Cash, Futures, and ETF prices (Levels and Log-Prices)

Variable	Mean (s.d.)	Min	Max	# of obs	Skewness	Kurtosis
Cash Price	113.86(24.16)	79.97	172.00	371	0.559	-0.600
Futures Price	113.74(2.12)	80.15	170.90	371	0.436	-0.677
ETF Price	31.35(2.16)	25.66	49.48	371	1.836	2.382
Log Cash Price	4.71(0.21)	4.38	5.15	371	0.244	-0.969
Log Futures Price	4.71(0.20)	4.38	5.14	371	0.131	-1.027
Log ETF Price	3.43(0.16)	3.24	3.90	371	1.591	1.641

Notes: Cash Price - Texas and Oklahoma, per 100 weight, ETF- iPath Bloomberg Livestock Subindex Total Return ETN.

Table 5.4 Summary Statistics of Diesel Cash, Futures, and ETF prices (Levels and Log-Prices)

Variable	Mean (s.d.)	Min	Max	n	Skewness	Kurtosis
Cash Price	3.41(0.62)	1.97	4.74	348	-0.419	-0.840
Futures Price	2.56(0.61)	1.16	4.10	348	-0.306	-0.7651
ETF Price	31.23(8.19)	17.80	65.68	348	1.783	4.7995
Log Cash Price	1.01(0.20)	0.68	1.56	348	-0.700	-0.522
Log Futures Price	0.91(0.26)	0.15	1.41	348	-0.730	-0.336
Log ETF Price	3.41(0.24)	2.88	4.18	348	0.635	1.454

Notes: Cash Price - Greenville, Mississippi, ETF- Teucrium Soybean Fund.

Unit Root and Cointegration Tests

The results for the Dickey Fuller unit root test on the log cash, futures, and ETF prices are given in Table 5.5. The Dickey Fuller test version for a single mean is used. For each price series for all four commodities, the null hypothesis of a unit root is not rejected based on both the rho and tau statistic at either the five percent or one percent level. This suggests that the price series are all nonstationary. To account for this unit root, it is appropriate to take the first difference of each series. Table 5.6 shows the results for the Dickey Fuller test on the differenced log prices. The results show that by taking the first difference the data no longer contains a unit root.

Table 5.5 Dickey Fuller Unit Root Tests for Corn, Soybeans, Live Cattle, and Diesel Log Cash, Futures, and ETF Price Series

Commodity	Price Series	Rho	Pr < Rho	Tau	Pr < Tau
Corn	**Cash**	-5.05	0.4278	-1.86	0.3518
	Futures	-3.99	0.5380	-1.57	0.4974
	ETF	-2.59	0.7060	-1.13	0.7036
Soybeans	**Cash**	-3.81	0.5578	-1.26	0.6471
	Futures	-2.67	0.6949	-1.01	0.7499
	ETF	-5.40	0.3941	-1.51	0.5256
Live Cattle	**Cash**	-1.06	0.8805	-0.51	0.8871
	Futures	-1.23	0.8632	-0.60	0.8671
	ETF	-7.40	0.2485	-2.93	0.0433
Diesel	**Cash**	-5.69	0.3709	-1.58	0.4912
	Futures	-4.27	0.5081	-1.30	0.6331
	ETF	-7.66	0.2332	-2.07	0.2570

Note: Single Mean Test.

Table 5.6 Dickey-Fuller Unit Root Tests for Corn, Soybeans, Live Cattle, and Diesel First Difference Log Cash, Futures, and ETF Price Series

Commodity	Price Series	Rho	Pr < Rho	Tau	Pr < Tau
Corn	**Cash**	-265.70	0.0001	-11.44	<.0001
	Futures	-230.20	0.0001	-10.65	<.0001
	ETF	-213.99	0.0001	-10.26	<.0001
Soybeans	**Cash**	-150.84	0.0001	-8.81	<.0001
	Futures	-151.86	0.0001	-8.88	<.0001
	ETF	-165.42	0.0001	-9.37	<.0001
Live Cattle	**Cash**	-531.38	0.0001	-16.25	<.0001
	Futures	-434.81	0.0001	-14.70	<.0001
	ETF	-400.25	0.0001	-14.08	<.0001
Diesel	**Cash**	-116.23	0.0001	-7.54	<.0001
	Futures	-308.43	0.0001	-12.35	<.0001
	ETF	-324.70	0.0001	-12.68	<.0001

Note: Zero Mean Test.

As mentioned in chapter IV, the price series must be checked for cointegration to determine if an error correction model is necessary when calculating hedge ratios. The two-stage Engle Granger cointegration test was used and the results from the second stage are given in Table 5.7. This stage checks the residuals of Equation (4.3) for a unit root using a Dickey Fuller test. These tests results show that cointegration is present between the logged cash and ETF price series for corn, soybeans, and diesel. The live cattle cash and ETF log price series are the only two price series that are not cointegrated. This is possibly due to the ETF being made up of lean hog futures contracts as well as live cattle futures.

The cointegrating relationship between the prices series can be visually seen in figures 5.1-5.4. These figures show the logged cash, futures, and ETF prices for each commodities. The reported ETF price is an adjusted per bushel price for comparison reasons, which was done by taking the logged per share price minus the average of the logged futures price. From figure 5.3 of live cattle cash, futures, and ETF logged prices, it can be seen that from the start of the time series to the end, the cash and ETF behave differently. The ETF price is decreasing, while the futures and cash prices are increasing.

Table 5.7 Two-stage Engle Granger cointegration test: Results of second stage Dickey Fuller test

Commodity	Price Series	Rho	Pr < Rho	Tau	Pr < Tau
Corn	**Cash - Futures**	-63.04	<.0001	-5.70	<.0001
	Cash - ETF	-20.51	0.0013	-3.25	0.0013
Soybeans	**Cash - Futures**	-72.99	<.0001	-6.25	<.0001
	Cash - ETF	-25.82	0.0002	-3.66	0.0003
Live Cattle	**Cash - Futures**	-68.59	<.0001	-5.79	<.0001
	Cash - ETF	-2.66	0.2622	-0.94	0.3107
Diesel	**Cash - Futures**	-52.25	<.0001	-5.04	<.0001
	Cash - ETF	-12.50	0.0135	-2.70	0.0069

Note: Zero Mean Test.

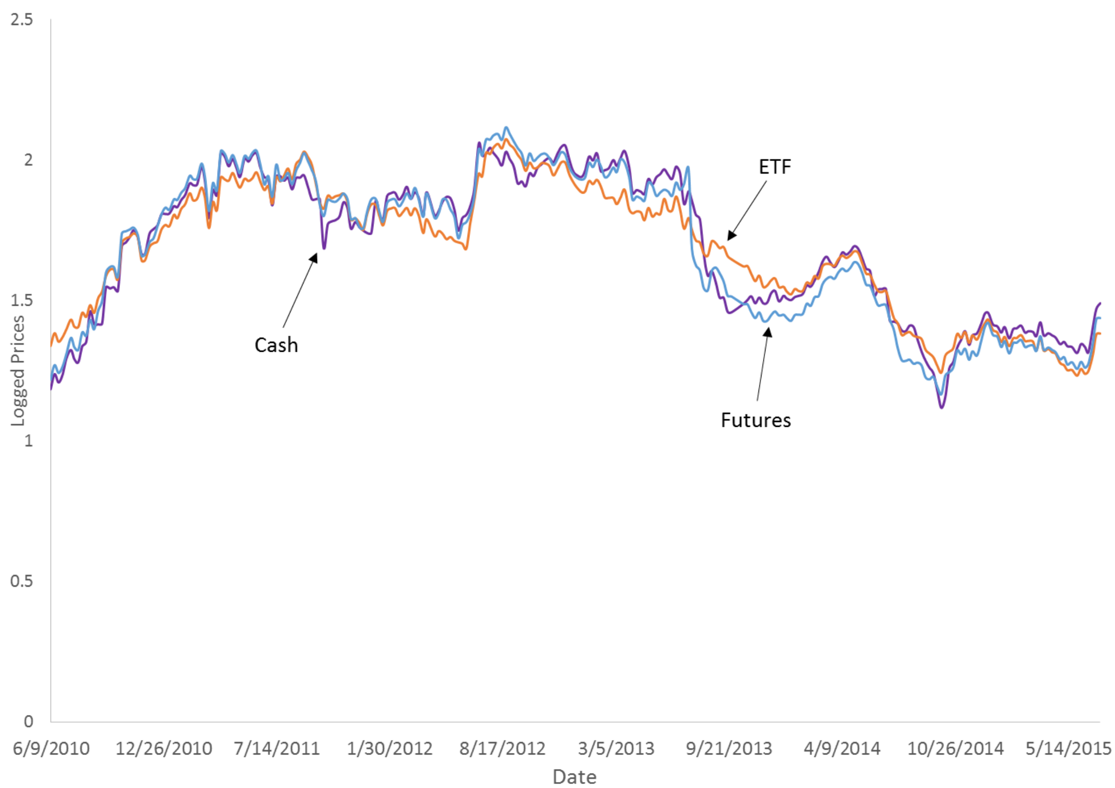

Figure 5.1 Corn Cash, Futures, and ETF Logged Prices

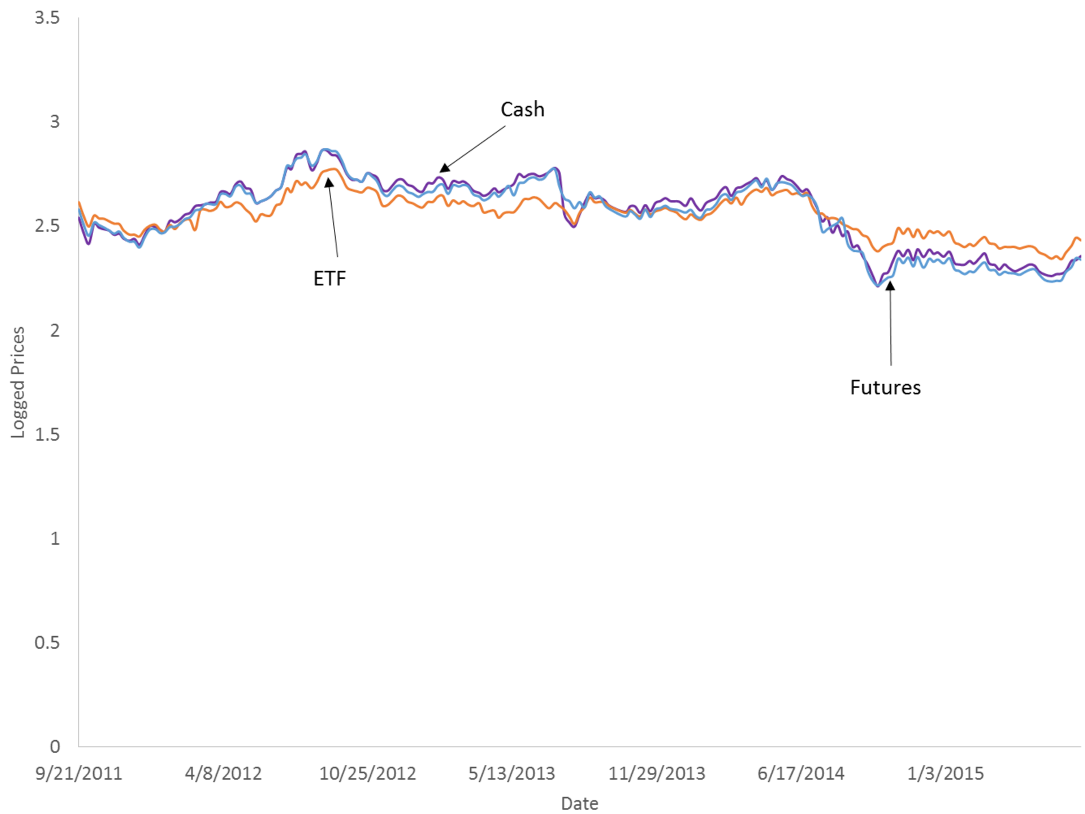

Figure 5.2 Soybeans Cash, Futures, and ETF Logged Prices

Figure 5.3 Live Cattle Cash, Futures, and ETF Logged Prices

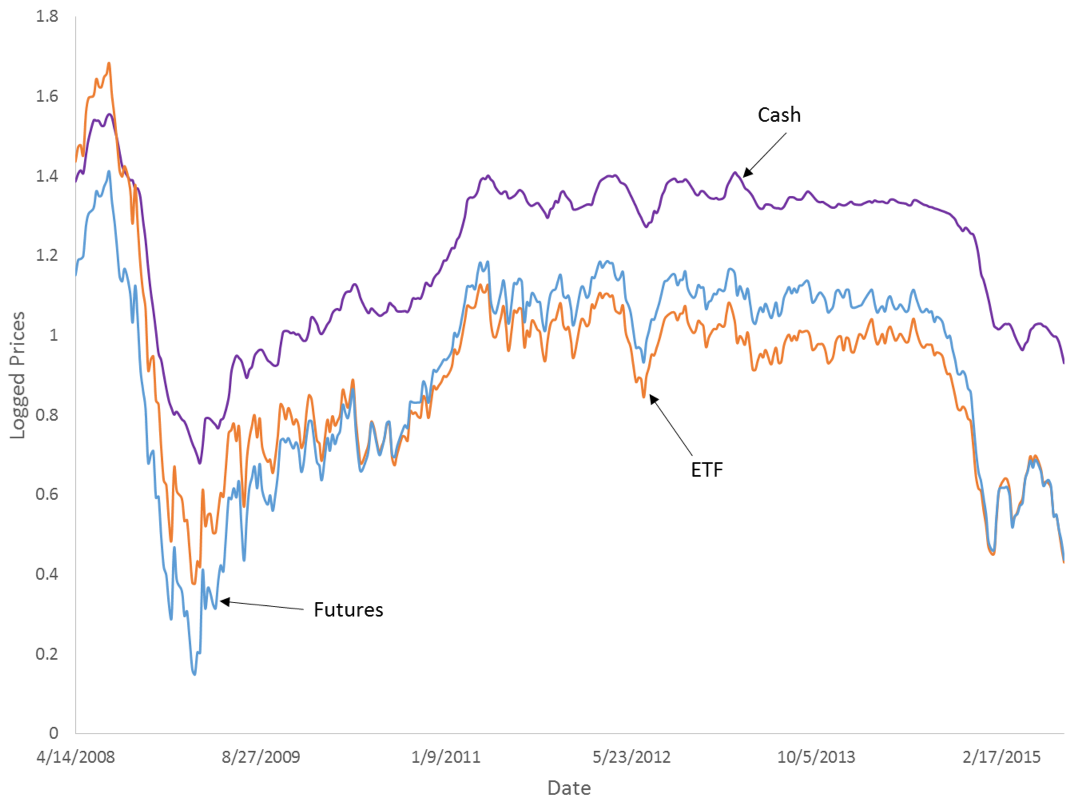

Figure 5.4 Diesel Cash, Futures, and ETF Logged Prices

Regression Results

The optimal hedge ratios estimated using the different regression methods for each commodity can be found in Table 5.8 along with the R-squared values of the models. Cointegration was not found to be present between the ETF and cash price series for live cattle. Therefore an ECM model was not used to find an optimal ETF hedge ratio for live cattle. The reported GARCH ratio is the average of the time-varying ratios found using the GARCH model. The time-varying ratios can be found in Figures 5.5- 5.12, along with the OLS and ECM estimates. These figures show the results of all three regression models used along with the mean of the GARCH hedge ratios. Futures hedge ratios and ETF hedge ratios were calculated over the same period of time for each commodity. The main takeaway from these figures is to see how the optimal hedge ratio will vary over time when using the GARCH model, while the OLS and ECM models are constant.

It was found that hedge ratios for futures and ETFs do not vary greatly across the different types of models. For corn futures, the GARCH model returns a higher optimal hedge ratio, but for a corn ETF hedge the OLS, ECM, and GARCH ratios are almost identical. The ECM and GARCH models for soybeans futures and ETFs result in higher hedge ratios than the OLS model. For live cattle, the GARCH model provides slightly greater hedge ratios than the OLS and ECM hedge ratios. The hedge ratios for diesel fuel are nearly identical across all three models for futures. The GARCH model returns a slightly high hedge ratio for ETFs than the OLS or ECM.

It was also found that an ETF hedge performs just as well as a futures hedge. For corn and soybeans the ETF hedge ratio is higher that the futures hedge ratio for each model. A *t*-test of OLS hedges also shows that the futures and ETF hedge ratios for corn and soybeans are statistically different. The hedge ratios for corn and soybeans also show that futures and ETFs do a good job covering a producer's price risk with hedge ratios near one. For example the Corn ETF hedge shows that a producer would want to hedge his total quantity of corn.

The ETF hedge ratio for live cattle and diesel are nearly identical to the futures hedge ratio for each model. Further, OLS hedges are not statistically different from each other. The futures and ETF optimal hedge ratios for live cattle range from 0.45 to 0.50.

The low diesel futures and ETF hedge ratios show that hedging diesel fuel using heating oil futures and ETFs perform poorly in protecting a producer against price risk.

The reported R-square values can be used to judge how well each model predicts. The ETF OLS model for corn has a higher R-squared value than the futures, but the ECM futures model has a slightly higher R-squared than the ETF model. The soybeans futures OLS model R-squared is higher than the ETF OLS model, while the ECM futures model is significantly higher than the ETF ECM model. The live cattle futures model R-square is higher than then ETF, and the diesel R-squared values are similar for both futures and ETFs.

Table 5.8 Regression Estimates of Futures and ETF Hedge Ratios for Corn, Soybeans, Live Cattle, and Diesel

	Hedge Ratios (R-Square)		
	OLS	**ECM**	**GARCH**
Corn			
Futures	0.78* (0.5878)	0.77* (0.6355)	0.82
ETF	1.02* (0.6101)	1.02* (0.6274)	1.03
Soybeans			
Futures	0.83* (0.5756)	0.87* (0.6889)	0.87
ETF	0.96* (0.5126)	0.99* (0.5319)	1.03
Live Cattle			
Futures	0.47 (0.3141)	0.48 (0.5250)	0.50
ETF	0.45 (0.2606)	n/a	0.49
Diesel			
Futures	0.15 (0.1806)	0.15 (0.7213)	0.16
ETF	0.15 (0.1746)	0.14 (0.6795)	0.17

Note: * denotes statistically significant difference.

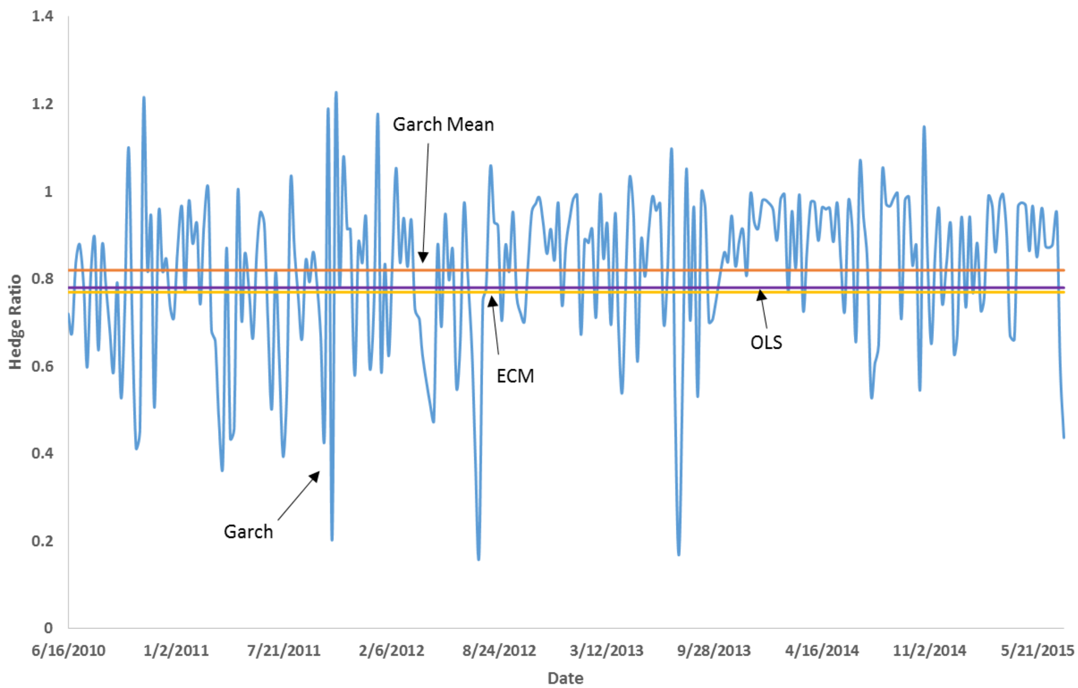

Figure 5.5 Corn-Futures Hedge Ratios

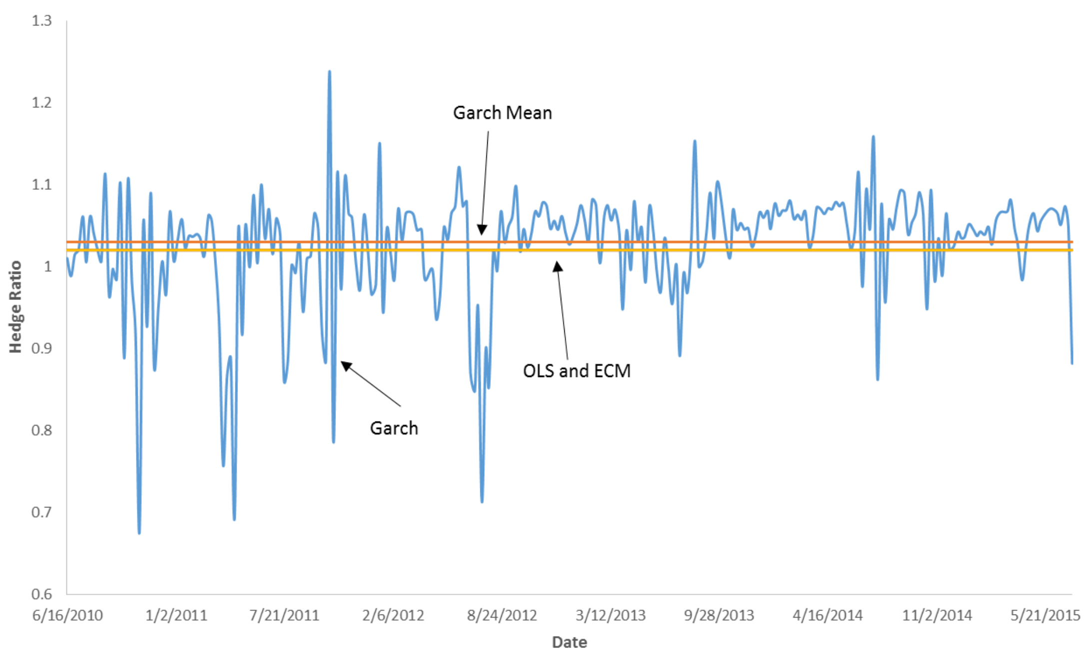

Figure 5.6 Corn-ETF Hedge Ratios

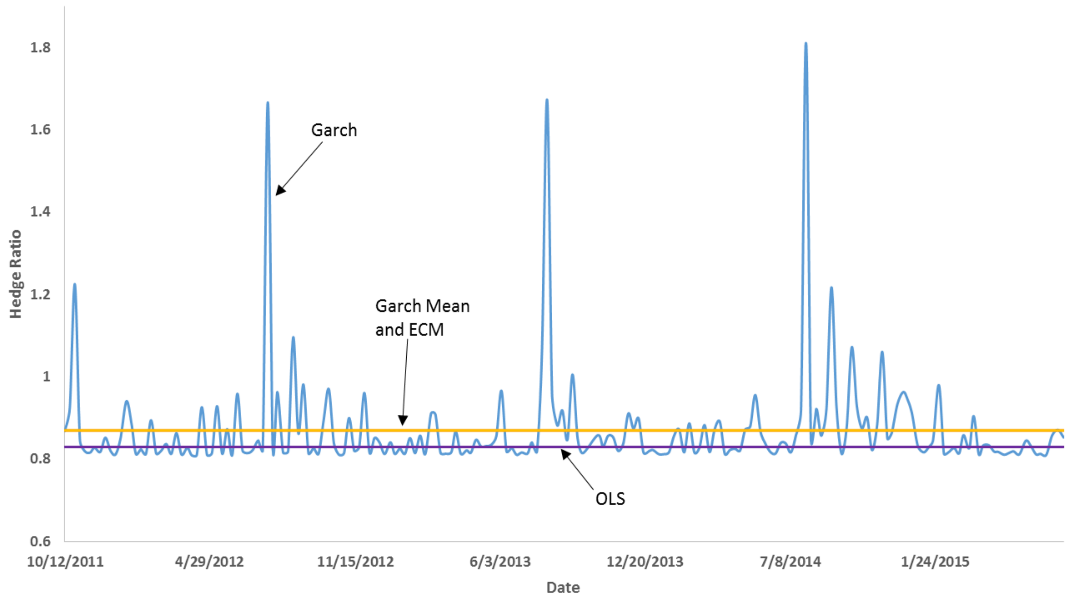

Figure 5.7 Soybeans-Futures Hedge Ratios

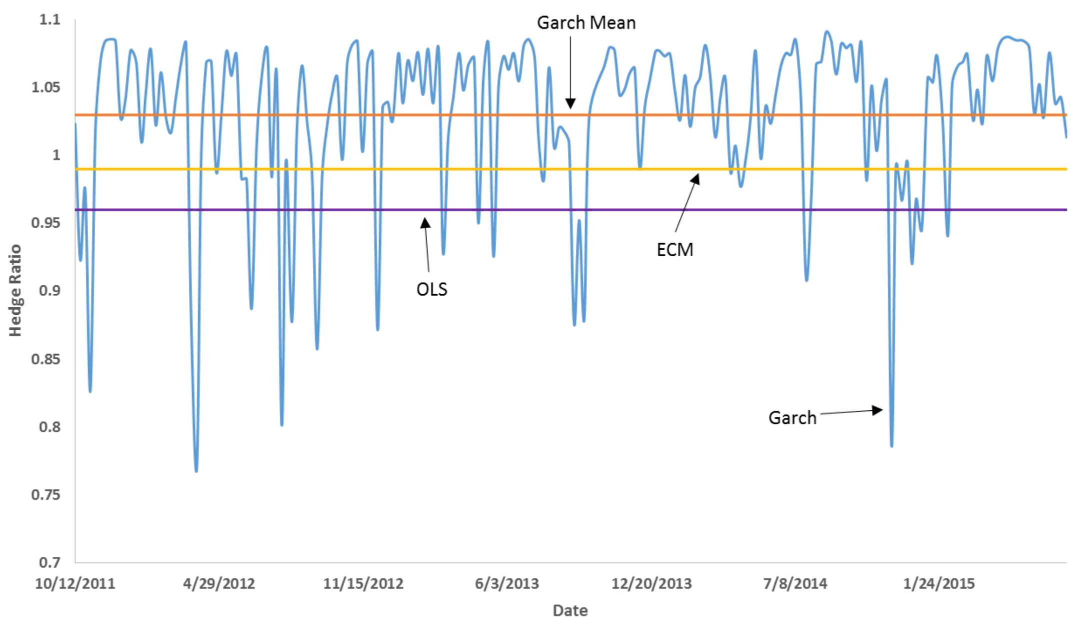

Figure 5.8 Soybeans-ETF Hedge Ratios

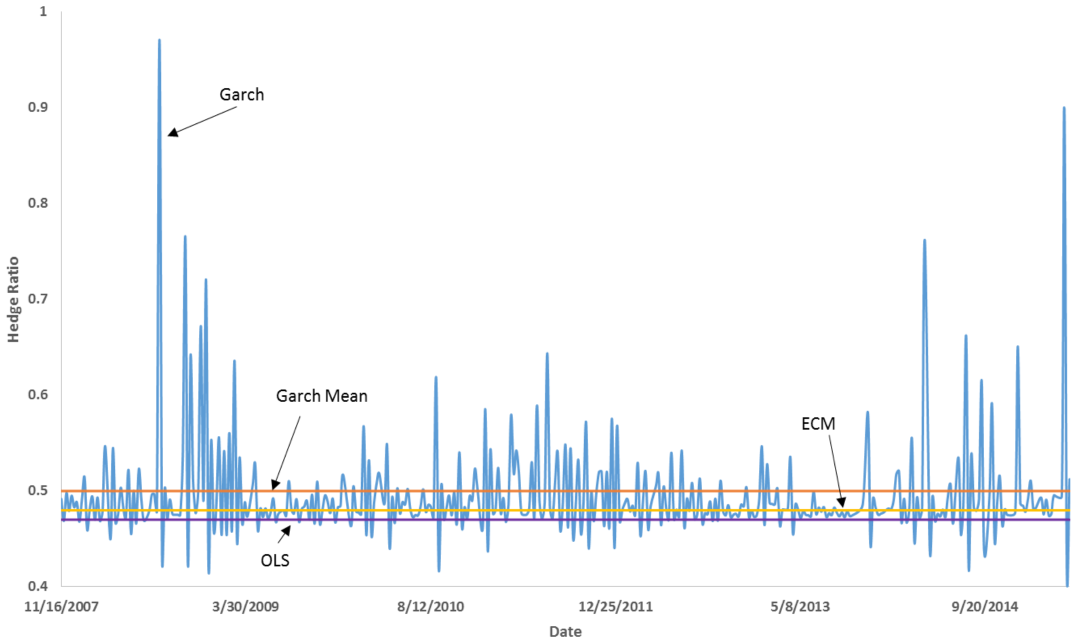

Figure 5.9 Live Cattle Futures Hedge Ratios

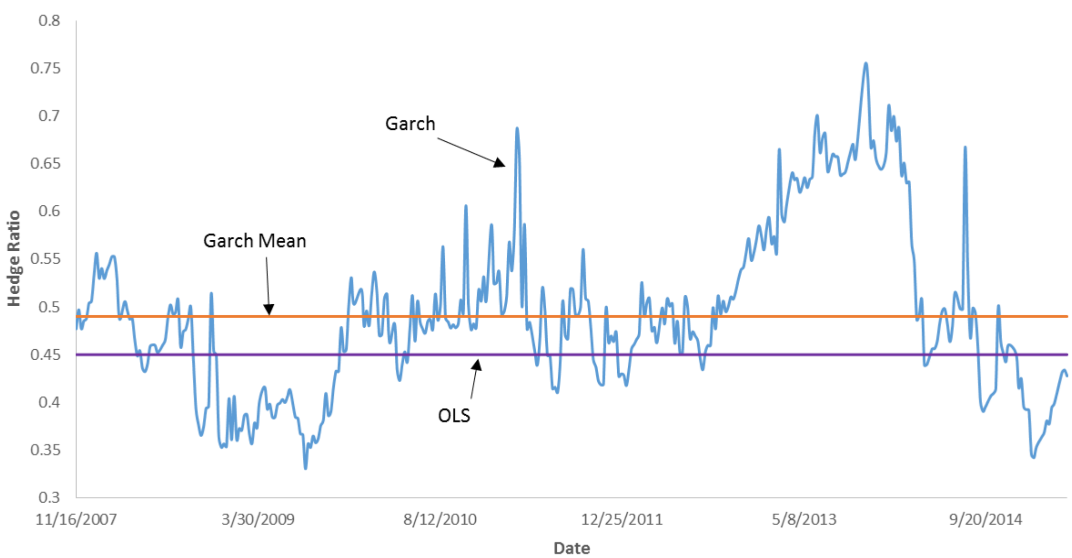

Figure 5.10 Live Cattle ETF Hedge Ratios

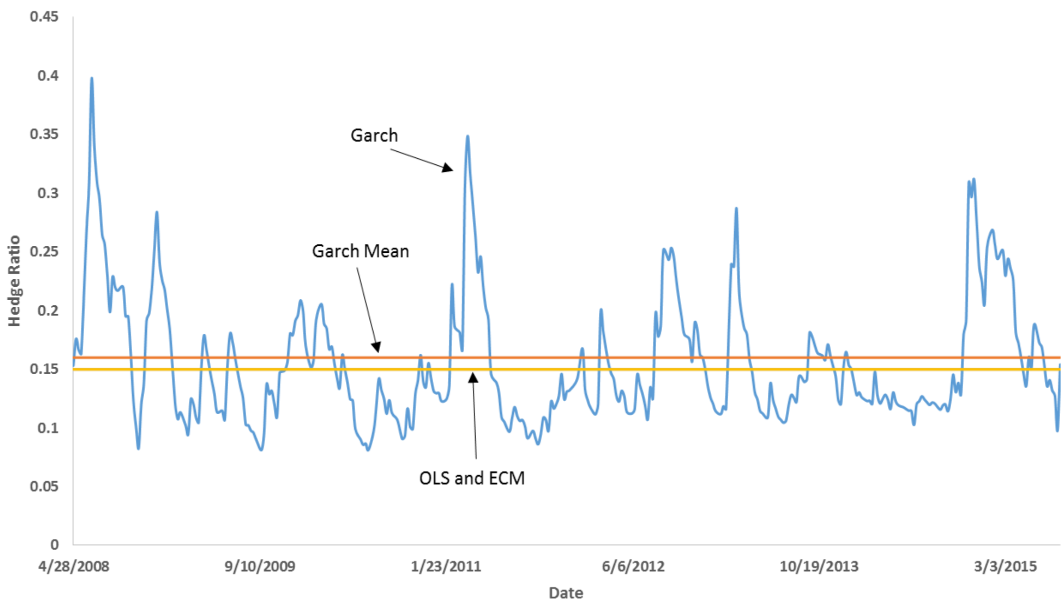

Figure 5.11 Diesel Futures Hedge Ratios

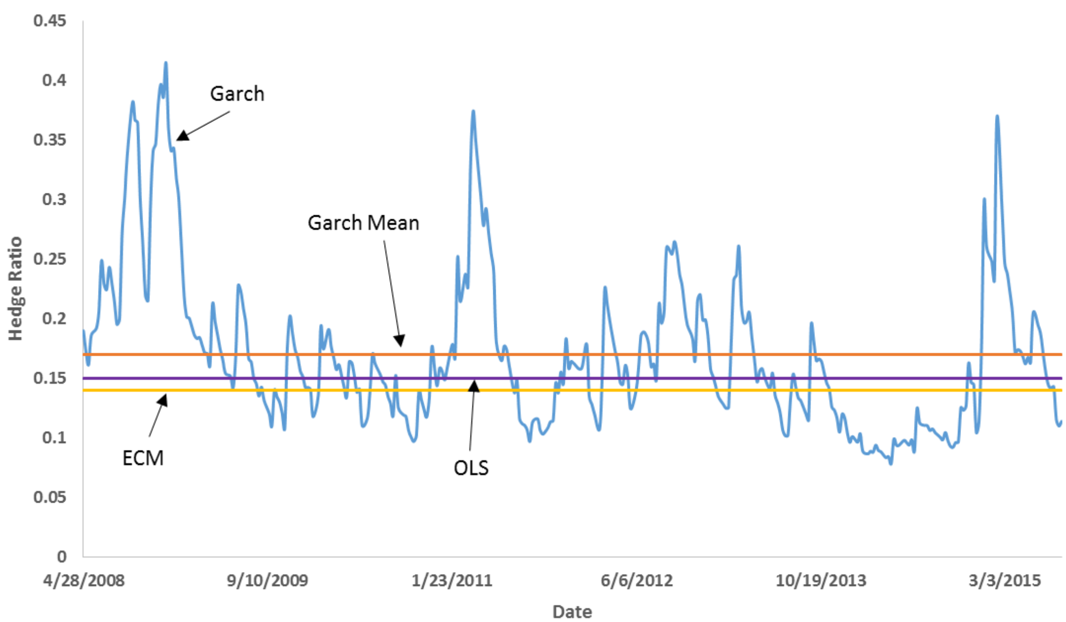

Figure 5.12 Diesel ETF Hedge Ratios

Simulation Results

The simulated cash, futures, and ETF price changes were used to calculate ending revenues, which were converted to utility values using a constant relative risk aversion utility function. From this, certainty equivalents were calculated and are shown in Figures 5.13 – 5.15 for various hedge ratios of each corn, soybeans, and diesel. These figures map out the certainty equivalents for each hedge ratio from 0 – 1.2 for both futures and ETFs. A hedge ratio of zero represents an unhedged position. The optimal hedge ratio corresponds to the maximum certainty equivalent. This will be the maximum point of the mapped out lines in the figures.

The optimal hedge ratio from simulation for a corn producer can be seen in Figure 5.13. The maximum certainty equivalent corresponds with a hedge ratio of 0.95 for futures and 0.825 for ETFs. The optimal hedge ratio for futures from simulations was higher compared to the optimal hedge ratios found using the regression techniques. This is because the simulation approach accounts for the risk averse behavior. The optimal ETF hedge ratio from simulations is lower than the optimal ETF hedge ratio found using regression techniques. This shows that in the presence of transactions costs the ETF hedge loses some of its effectiveness. The certainty equivalent is higher for a futures hedge than an ETF hedge, meaning a producer is better off placing a futures hedge.

The optimal soybean hedge ratio for futures from simulations is higher compared to the optimal hedging ratios from regression techniques. This is again because the simulation approach accounts for the risk averse behavior. The optimal soybean hedge ratios from simulation can be found in Figure 5.14. It can be seen in this figure that the corresponding optimal hedge ratio for the maximum certainty equivalent for a futures hedge is 0.95 and the ETF hedge is 0.65. While the futures optimal hedge ratio is higher than the optimal hedge ratios from the regression techniques, the ETF hedge ratio is lower than the regression findings. This shows that an ETF hedge of soybeans loses some effectiveness in the presence of transaction costs just as corn did. Also like corn, the certainty equivalent for the optimal futures hedge ratio is higher than the optimal ETF hedge ratio. A producer would again be better off hedging using futures than ETFs if they are available.

Figure 5.15 shows the optimal diesel hedge ratios from simulation. As was the case with corn and soybeans, the futures hedge again outperforms the ETF hedge. The optimal hedge ratios from the utility maximizing framework are larger than from the regressions. Futures are a perfect one to one hedge. The optimal ETF hedge ratio of 0.80 is a great improvement on the regression results. The simulation results show that diesel fuel could be effectively hedged over the specified time period using heating oil futures or ETFs. The certainty equivalents for the futures hedge is again higher than the ETF hedge.

To further investigate which transaction costs have the greatest effect on the optimal hedge ratio, the simulations were performed again using different transaction cost structures. Table 5.9 summarizes these results for the three commodities. Five different cases were investigated and included 3 percent annual interest rate (down from 6 percent), no brokerage fees, no expense ratio, inclusion of a margin call for futures, and no transaction costs.

As is expected, when there are no transaction costs for placing a corn hedge, both the futures and ETF hedge improves. When lowering the interest rate to 3 percent, the optimal hedge ratio improves for ETFs. Removing the expense ratio improves the optimal ETF hedge ratio by the largest margin of all the cases looked at. Inclusion of a $1,500 margin call on futures had no effect on the optimal futures hedge ratio.

The various transaction costs affect optimal soybean hedge ratio in the same manner. When no transaction costs are included, both the futures and ETF optimal hedge ratios increase. Lowering the interest rate and excluding an expense ratio both improve the optimal ETF hedge ratios. Inclusion of a $2,300 margin call does slightly decrease the optimal futures hedge ratio. Having no brokerage fees also increase the optimal hedge ratios.

For diesel, when the interest rate is decreased the optimal ETF hedge ratio improves. Also when the expense ratio is removed, the optimal ETF hedge ratio improves slightly. The removal of brokerage fees have no effect on the optimal hedge ratio for either futures or ETFs. The inclusion of a margin call of $4,200 has no effect on the optimal futures hedge ratio. The removal of all transaction costs improves the optimal ETF hedge ratio to be greater than the optimal futures hedge ratio. This shows that the transactions cost of placing an ETF hedge do impact the effectiveness of the hedge.

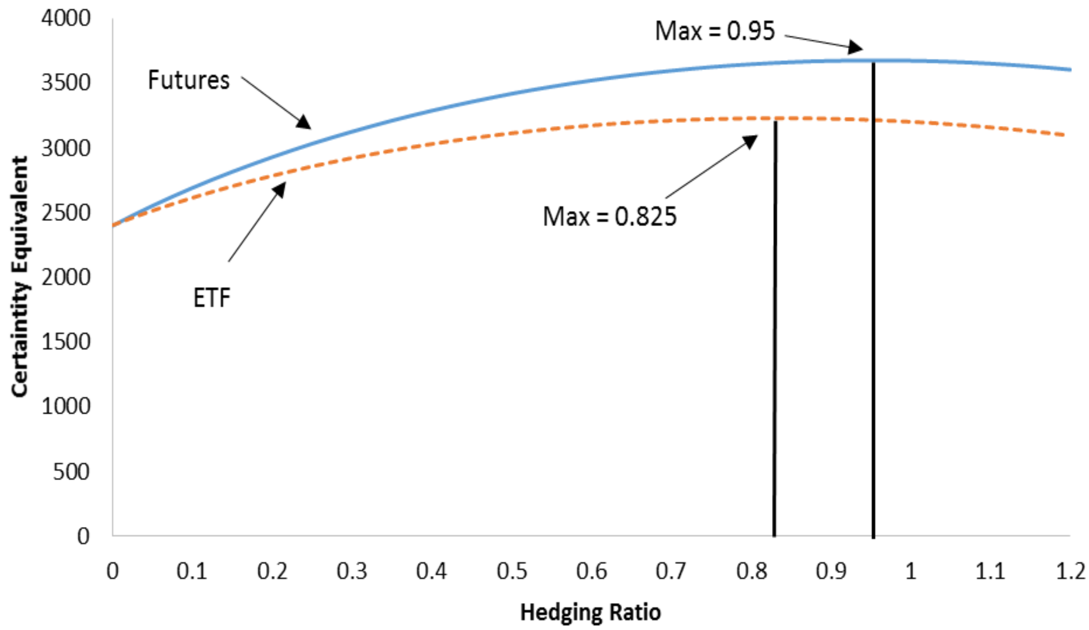

Figure 5.13 Corn Hedge Ratios from the Simulation Approach

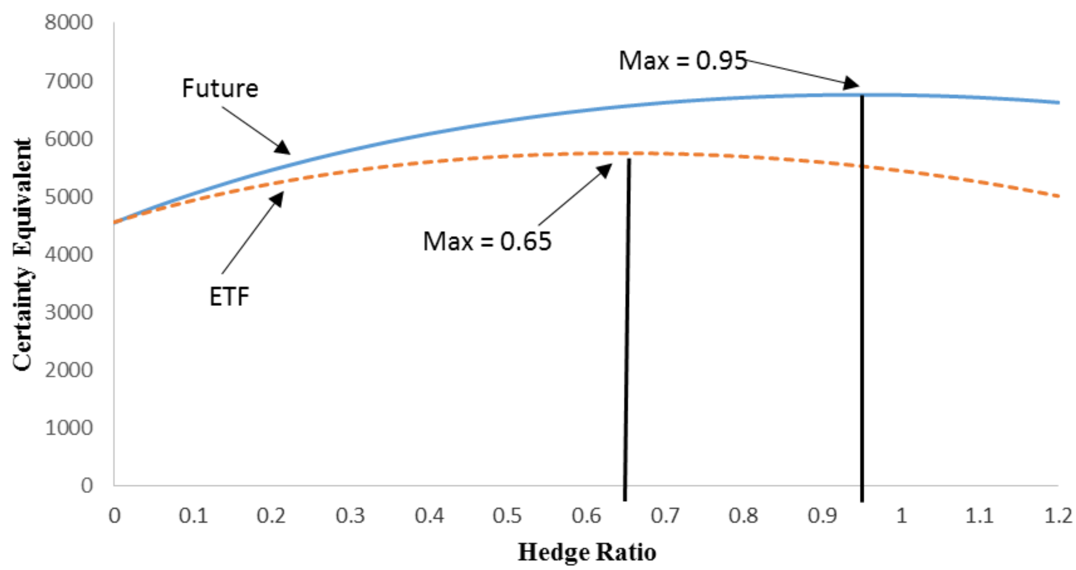

Figure 5.14 Soybean Hedge Ratios from the Simulation Approach

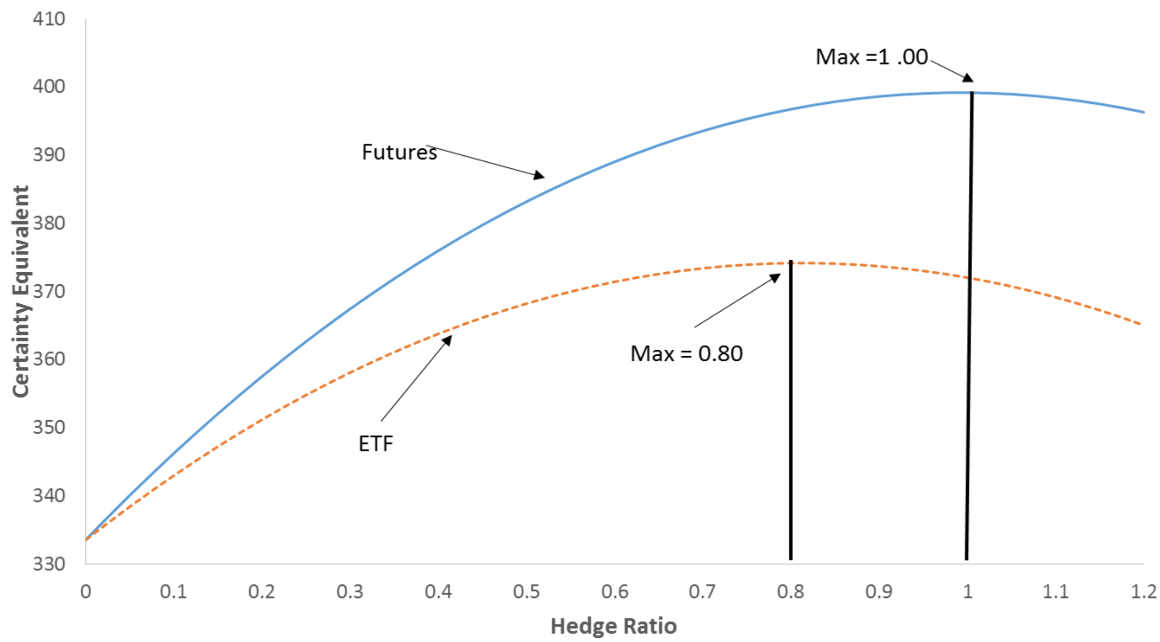

Figure 5.15 Diesel Hedge Ratios from the Simulation Approach

Table 5.9 Effects of Transaction Costs on the Optimal Hedge Ratio

Commodity	Futures Hedge Ratio	ETF Hedge Ratio
Corn		
Original	0.95	0.85
3% Interest Rate		0.925
No Expense Ratio		0.975
Margin Call	0.95	
No Brokerage Fees	1.00	0.90
No Transaction Costs	1.00	1.10
Soybeans		
Original	0.95	0.65
3% Interest Rate		0.75
No Expense Ratio		0.75
Margin Call	0.925	
No Brokerage Fees	1.00	0.675
No Transaction Costs	1.00	0.95
Diesel		
Original	1.00	0.80
3% Interest Rate		0.925
No Expense Ratio		0.825
Margin Call	1.00	
No Brokerage Fees	1.00	0.80
No Transaction Costs	1.00	1.05

CHAPTER VI

CONCLUSIONS

This study has investigated the effectiveness of Exchange Traded Funds as a hedging tool. OLS, ECM, and GARCH regression models were used to find optimal hedge ratios for corn, soybeans, live cattle, and diesel fuel. Simulations were used to find the optimal hedge ratios for corn, soybeans, and diesel fuel for a risk averse producer and in the presence of transaction costs.

Based on regression results, an ETF hedge of corn and soybeans outperforms a futures hedge. A potential reason for this outperformance maybe that the corn and soybean ETFs incorporate more information available from the futures market by being composed of multiple futures contracts. On the other hand, hedging with futures only uses the information from a single futures contract. The diesel ETF incorporates information from a single futures contract as it is composed of only the nearby futures contract. This could account for the similar futures and ETF hedging ratios in the case of diesel fuel.

Simulations show a different outcome though. Across all three commodities, the futures hedge outperforms the ETF hedge. This highlights the effects of higher transaction costs of ETFs as compared to futures. The higher transaction costs of ETFs, due to paying loan interest and a management fee for holding the fund, offset some of the effectiveness of the ETF hedge. This loss of effectiveness should not deter a small producer from placing an ETF hedge though, due to the fact that they have no other reliable risk management tool available, and ETFs still provide a reasonable level of price risk protection.

This study is one of the first to show that ETFs can be used to effectively hedge a producer's price risk. These finding will be able to greatly help small producers who are currently left with no protection from the volatility of commodity markets. As noted earlier, 34 percent of Mississippi corn producers and 46 percent of Mississippi soybean producers would benefit from the ability of ETF hedging due to their small production size. This study also benefits producers by showing that ETFs would provide a reliable way to hedge diesel fuel price risk. An ETF hedge would benefit at least 89 percent of Mississippi row crop producers due to the quantity requirement needed to place a futures hedge.

With futures based ETFs shown to be an effective risk management tools, it could lead to the creation of ETFs for other commodities that have futures markets. One that would benefit Mississippi and the Southeast would be using a feeder cattle futures contract. It was shown that a live cattle futures based ETF can effectively hedge price risk, therefore it would be reasonable to expect that a feeder cattle ETF could do the same.

This study is a first to highlight the use of ETFs as a hedging tool for agricultural producers. The finding should encourage more interest in researching the potential benefits ETFs can have. An extension of this research would be to look at various other locations. Mississippi is not a large corn growing state, and it would be interesting to see if these results hold in the Corn Belt states like Iowa and Illinois. There also exist ETFs for other commodities such as wheat, cotton and sugar cane. On the input side, ETFs could possibly be used to hedge a producer's fertilizer price risk. Other ETFs exist that are stock based instead of futures based ETFs. These ETFs exist for various commodities, and it would be interesting to see if they can be used to hedge as effectively as a futures based ETF. A further extension of the simulation approach can be to see how varying degrees of risk aversion effect the optimal hedge ratio.

This study has shown that ETFs have the potential to be used as an effective price risk management tool just as futures contracts have been used for years. This would provide small producers who are disadvantaged due to production size with an effective risk management tool.

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