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Using the Crude Oil and Heating Oil Markets for Diesel Fuel Purchasing Decisions

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Agricultural producers and input suppliers must regularly make decisions based on forecasts; however, most publicly available forecasts are for outputs. Research has shown the importance of being a low-cost operator. Thus, focusing on inputs may be beneficial. The objective of this research was to estimate models based on futures markets to forecast diesel fuel prices. Results suggest diesel fuel prices forecasted using the crude oil or heating oil futures market are reasonably accurate, and that this approach is superior to using a historical average. Based on out-of-sample price predictions, producers could profitably use crude oil futures-based models to make diesel fuel purchasing decisions. While the gains from following a model-based decision rule were small, they were positive, suggesting producers would not be worse off following this strategy.

Key Words: crude oil, diesel fuel, forecasts, forward contracting, heating oil

Managing the risks in their businesses has always been important for agricultural producers. However, because the 1996 and subsequent 2002 Farm Bills increased producers' planting flexibility and decoupled government payments, there has been an increased producer emphasis on risk management. For example, the Risk Management Agency (RMA) was created in the 1996 Farm Bill to oversee federal crop insurance and the development of programs involving revenue insurance or the use of futures and options markets to manage risk [U.S. Department of Agriculture (USDA), 1996]. Much of the recent focus pertaining to risk management has been on marketing and crop insurance strategies (e.g., Coble, Heifner, and Zuniga, 2000; Dhuyvetter and Kastens, 1999; Wisner, Blue, and Baldwin, 1998; Zulauf and Irwin, 1998).

It is important for producers to keep in mind that profitability is simply the difference between revenue and expenses, and thus profitability risk is a function of both income and costs. For crop producers, revenue comes from crop sales, government payments, and insurance indemnity payments. Expenses are incurred for both direct

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production inputs (e.g., seed, fertilizer, chemicals, fuel) and fixed inputs (e.g., labor, management, and asset charges). While the emphasis in risk management research has tended to be on revenue (yields and prices), it may be that producers could benefit from focusing their management efforts on expenses.

In a study of payoffs to farm management, Nivens, Kastens, and Dhuyvetter (2002) found managing for lower production costs consistently earned higher profits than managing for higher prices. Specifically, they concluded that producers who were in the bottom third of costs (i.e., low cost) consistently had higher profits than producers in the top third of prices received (i.e., high prices), ceteris paribus. Furthermore, they found it was easier for producers to differentiate themselves from other producers with regard to cost as opposed to price. Thus, not only was cost control more profitable, but it was easier to achieve.

Sonka, Hornbaker, and Hudson (1989) and Mishra, El-Osta, and Johnson (1999) reported similar results for grain farms—i.e., being a low-cost operator was generally more important for success than focusing on marketing. However, based on their farm-level analysis, Mishra and Perry (1999) concluded that producers who forward contract inputs reduce risk and may be able to secure better pricing on contracted inputs. Therefore, it may be advantageous for producers to analyze purchasing strategies for managing price risk associated with production inputs. Likewise, producers may also benefit if agribusinesses/input suppliers can identify strategies for reducing their market risk.

The variability of energy prices generally, and crude oil prices specifically, has increased considerably in the last four to five years compared to much of the 1990s (figure 1). Crude oil prices directly impact the prices of crop inputs such as chemicals and fuel and oil because crude oil is a primary feedstock in the production of these inputs. Crude oil prices also impact the prices of many other production inputs indirectly through their effect on transportation and processing costs.

Williams and DeLano (2000) estimated that production costs for an average farm in southwest Kansas would increase \$9,354 (\$8.83/acre) given the \$12.69 per barrel crude oil price increase from June 1999 to June 2000. Sixty-eight percent of this cost increase was due to higher diesel and oil prices, with the remaining 32% coming from higher costs of other inputs (e.g., seed, fertilizer, chemicals). Thus, rising crude oil prices impact agricultural producers in more ways than simply increasing the cost of diesel fuel, but the effect on diesel prices is likely the most immediate and visible, and consequently of interest to producers.

As crude oil prices in 2000 rose to their highest levels in a decade, producers began asking what these higher energy prices would mean in terms of diesel fuel prices. Having access to price forecasts for crop inputs such as diesel fuel is useful for producers when making management decisions. For example, price forecasts allow producers to: (*a*) convey to their lenders an estimate of operating capital requirements for the upcoming year; (*b*) determine optimal crop mix and input use (e.g., optimal irrigation amounts); and (*c*) make production decisions regarding management practices (e.g., level of tillage, dryland versus irrigation, harvest date). Another question pondered by some producers in the fall of 2000 was whether they should forward

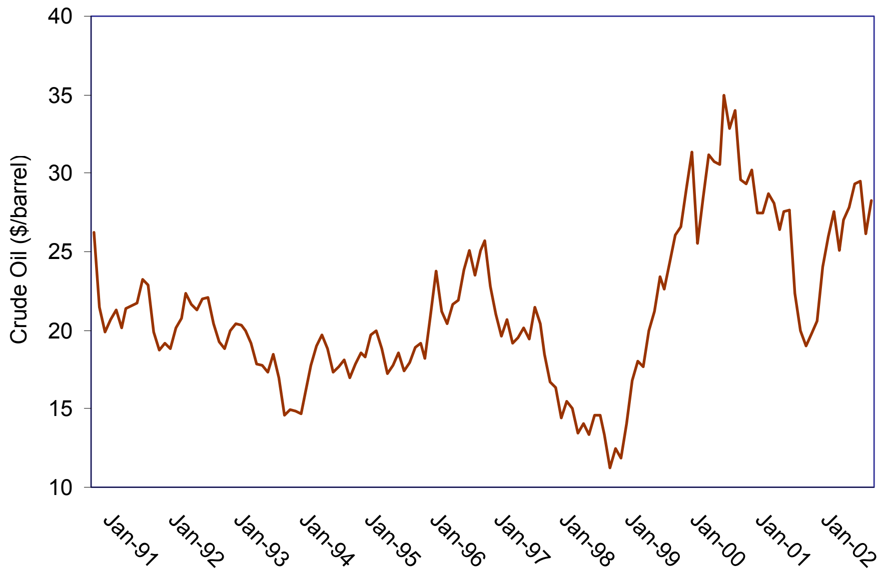

Figure 1. Monthly average NYMEX nearby crude oil futures price, 1991–2002

contract inputs for 2001 production needs. In addition to their value to producers, diesel fuel forecasts are also useful for agribusinesses (i.e., input suppliers) because these suppliers must make buy/sell decisions.

The objectives of this study are to develop a better understanding of the relationship between oil and diesel fuel prices and to determine if producers and agribusinesses can benefit from an awareness of this relationship. Toward this end, we specifically propose to: (*a*) identify historical seasonal price patterns for diesel fuel, as this information is seldom reported publicly; (*b*) examine historical relationships between diesel fuel prices and the crude oil and heating oil futures prices and develop simple models that producers and input suppliers can use to make real-time price forecasts; and (*c*) determine if real-time forecasts could be used in a systematic manner for making forward purchasing decisions to increase profits.

Background

If producers anticipate prices for crop inputs will increase in the future or if they want to reduce input price variability, then a possible management strategy is to forward contract future input needs. Based on the findings of Mishra, El-Osta, and Johnson (1999), farms that forward contract inputs are more likely to have higher returns compared to farms not forward contracting. They attribute this result to possible increased efficiency of resource use and price breaks associated with forward contracting, and not to "beating the market."

In order to make informed decisions about forward contracting, producers need to have some price forecast data indicating where future price levels might be, relative to current prices. Price forecasts for major crops and livestock are readily available from the USDA, universities, market advisory services, farm magazines, etc. However, forecasts for crop inputs such as diesel fuel typically are much more difficult to find. Although the Department of Energy provides a monthly U.S. average diesel fuel price forecast, diesel price levels and seasonal patterns can vary between geographical locations (Conley, 1994). Thus, more localized diesel price forecasts are needed. Two important questions arise: Where can producers and input suppliers obtain price forecasts for crop inputs? and Can the price forecasts be used to make profitable decisions in real time?

Forecasting models can be simple (e.g., a historical mean), or extremely complex (e.g., a multinomial first-differenced distributed lag model). Because historical prices for many crop inputs are less readily available than crop prices, producers in many cases may not even be aware of simple historical market patterns such as seasonal price patterns and long-term trends. While this information may represent simplistic "models," identifying this basic information may be useful to producers and input suppliers as they make their production and purchasing decisions.

Using input from interviews with extension economists, Anderson and Mapp (1996) reported that producers want simple, easy to use, decision rules. Therefore, the more complex a model becomes, the less likely it will be used. For example, structural models requiring ancillary forecasts of explanatory data are of little value to an individual needing to make production or inventory decisions based on real-time input price forecasts with limited information available.

Kastens, Jones, and Schroeder (1998) compared various simple-to-construct forecasting methods and concluded that a deferred futures plus historical basis forecast method was the most accurate for most commodities considered. Their findings indicated more complex regression-based models did not increase accuracy, and the added sophistication of these models was not merited. Comparing alternative methods of forecasting basis, Dhuyvetter and Kastens (1998) concluded that simple models (historical averages) were as accurate as more complex models. Thus, evidence clearly suggests relatively simple models to forecast input prices may be useful for producers as a source of information for making production and marketing decisions.

An example of a simple forecasting model is one that relies on the futures market because this information is readily available with very little cost to producers. However, from the standpoint of a producer or agribusiness, the relevant issue is not simply the cost of obtaining a forecast, but also the accuracy of the forecast. Specifically, the cost or simplicity of a forecast means little if the forecast cannot be used to make profitable management decisions.

Tomek (1997) concluded that futures prices can be viewed as forecasts and noted it is difficult for structural or time-series econometric models to improve on futures market forecasts. If futures markets are efficient, there is no reason to expect hedging will improve either selling or purchasing prices, but the futures market can be used for information. Zulauf and Irwin (1998) suggest the use of futures markets as a source of information rather than as a trading medium. In their analysis of price forecasting and marketing strategies, Brorsen and Irwin (1996) argue that extension economists should rely on the futures market to provide the price forecasts needed in outlook programs. Further, producers use the futures market in forming price expectations (Schroeder et al., 1998). Assuming crop input markets are also characterized by efficient markets, it therefore seems appropriate to encourage producers and input suppliers to use futures-based price forecasts for crop inputs to assist them in making their production and purchasing decisions.

Empirical Models

One method of forecasting cash prices which relies on using the futures market for information is to simply consider the historical relationship between these two price series by estimating the following equation:

$$\text{(1)} \qquad \textit{Cash Price}_t = \beta_0 + \beta_1 \textit{Futures Price}_t ,$$

where β_0 represents a fixed difference between the two series (i.e., basis), and β_1 represents how the two prices move together. If the difference between the two prices is not constant throughout the year, then monthly dummy variables should be added to the right-hand side of (1), allowing the basis to vary seasonally. Alternatively, the equation could be estimated separately for each futures contract. Furthermore, although the cash and futures prices in equation (1) are represented as being contemporaneous, a lag may be justified to allow for time associated with processing. While equation (1) might be estimated to predict cash prices conditional upon some futures price, it has also been used to estimate the minimum variance hedge ratio (β_1).[1]

Because our objective is to estimate empirical futures-market-based models that can be used for forecasting the cash price of diesel fuel, the relationship demonstrated in equation (1) is appropriate. Futures contracts considered here are crude oil and heating oil—both of which are traded on the New York Mercantile Exchange (NYMEX). Diesel fuel used by agricultural producers and heating oil are close substitutes, so it is assumed the prices of these two commodities will move together. Furthermore, because diesel fuel and heating oil are both derivatives of crude oil, the prices of all three are expected to move together. Based on these expected relationships, the following models are defined:

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[1] There has been debate as to whether equation (1) should be estimated in levels, price changes, or percentage price changes if the β_1 is to be interpreted as a minimum variance hedge ratio. Witt, Schroeder, and Hayenga (1987) argue that optimal hedge ratios generated by price-level regressions are as statistically correct as those estimated with price changes or percentage changes. They state that for an anticipatory hedge (as opposed to a storage hedge), estimating the equation in levels is theoretically sound. However, Myers and Thompson (1989) contend that estimating equation (1) in levels is not appropriate and would lead to errors in the optimal hedge ratio. Because the focus of this study is on using equation (1) for predicting prices, and not for estimating the optimal hedge ratio, it is estimated in levels.

$$(2) \qquad \textit{Diesel Price}_t = \beta_0 + \beta_1 \textit{NYMEX Crude Oil}_t + \varepsilon_t,$$

$$(3) \qquad \textit{Diesel Price}_t = \alpha_0 + \alpha_1 \textit{NYMEX Heating Oil}_t + \varepsilon_t,$$

where *Diesel Price* is the diesel fuel cash price (purchase price for producer and selling price for supplier); *NYMEX Crude Oil* and *NYMEX Heating Oil* represent nearby futures market prices; t is a time index indicating the cash and futures prices are contemporaneous; ε represents an error term; and β_0, β_1, α_0, and α_1 are parameters to be estimated. Equations (2) and (3) are both considered to empirically determine which futures contract—crude oil or heating oil—might perform better for predicting the price of diesel.[2] These equations could also be estimated with monthly dummy variables added to test if the basis (i.e., intercept) varies seasonally.

From a producer's perspective, equations (2) and (3) are appealing because once they are estimated they provide a relatively easy way to forecast the price of diesel fuel while relying on a key economic principle—the principle of an efficient futures market. That is, the price forecasts rely on the futures market as a source of information.

Data

Publicly reported data for crop inputs are much less readily available than for other commodities.[3] A continuous time series of monthly average diesel fuel prices was obtained from a fuel supplier in southwest Kansas for the period January 1994 through December 2002 (Gerber Oil, Inc., 2002). In addition to the cash prices, monthly average nearby futures prices for crude oil and heating oil were collected (Commodity Research Bureau, 2003). Futures contracts are traded for each month of the year for crude oil and heating oil. Contracts stop trading in the month preceding delivery. Thus, the nearby contract being traded in the month of January is the February contract (January contract expires in late December), the nearby in February is the March contract, and so on.

Table 1 reports summary statistics for the three different prices series. Nearby crude oil futures prices averaged \$21.59 per barrel and ranged from a low of \$11.21 to a high of \$35 over the nine-year period. Nearby heating oil futures prices averaged about 59¢ per gallon and ranged from a low of 31.2¢ to a high of \$1.02 per gallon. Monthly cash diesel fuel prices averaged almost 84¢ per gallon over this time period and ranged from a low of 55¢ to a high of \$1.23 per gallon. As measured by the coefficient of variation (CV), the variability of crude oil and heating oil futures prices was similar, whereas cash diesel prices exhibited less variability.

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[2] Both markets are considered because while heating oil is a close substitute for diesel, the crude oil futures market typically has more volume than the heating oil market, and consequently may be more effective and practical for predicting diesel prices.

[3] The Kansas Agricultural Statistics Service reported monthly average diesel fuel prices prior to 1986. From 1986 through 1994, prices were reported on a quarterly basis, and since 1995, prices are reported only once per year (in April).

Table 1. Summary Statistics for Monthly Price Variables Used in the Estimation, 1994–2002

Variable[a]	Unit	Mean	Standard Deviation	Coeff. of Variation	Minimum	Maximum
NYMEX Crude Oil (futures)	$/barrel	21.5850	5.4907	0.2544	11.2100	35.0000
NYMEX Heating Oil (futures)	$/gallon	0.5876	0.1511	0.2573	0.3120	1.0200
SW Kansas Diesel (cash)	$/gallon	0.8366	0.1639	0.1959	0.5500	1.2300

[a] *NYMEX Crude Oil* = New York Mercantile Exchange nearby crude oil futures price, *NYMEX Heating Oil* = New York Mercantile Exchange nearby heating oil futures price, and *SW Kansas Diesel* = southwest Kansas bulk delivered diesel fuel price.

Figure 2 presents a graph of the historical prices for the commodities listed in table 1. Examining the data visually helps identify if there are long-term trends in place and also gives an indication of whether the models to be estimated might have some validity. Kansas diesel fuel prices fluctuate with both the heating oil and crude oil NYMEX futures prices.

Seasonal patterns in prices are driven by fundamental factors, and if markets are efficient it is generally not possible to profit from these price patterns. However, because historical prices for crop inputs are seldom reported, many producers may not be aware of seasonal price patterns. In other words, while the market may be efficient at the aggregate level, it may not be as efficient on a localized level due to a lack of information. Thus, individual producers may make incorrect decisions pertaining to forward pricing solely due to lack of information. In this case, simply having knowledge of historical seasonal price patterns may be of use to producers.

Figure 3 shows seasonal price indices for crude oil, heating oil, and diesel fuel. All three price series follow a seasonal pattern characterized by low prices in the spring which strengthen as the year progresses, peaking in September and then decreasing through the end of the year. Based on the seasonal indices, Kansas diesel fuel prices appear to follow NYMEX crude oil futures prices slightly better than heating oil futures prices.

Conley (1994) hypothesized that the relationship between diesel fuel prices in the Northern Plains and crude oil futures prices is likely stronger than diesel prices and heating oil because of the different delivery points—i.e., the delivery point for crude oil futures is Cushing, Oklahoma, and the delivery point for heating oil futures is the New York harbor. However, Cushing's results, based on data from 1988–1992, indicated crude oil was less effective than heating oil at hedging diesel fuel in Scott City, Kansas.

Modeling Issues

When working with time-series data, such as used to estimate equations (2) and (3), there are several potential concerns if we want to make inferences from the estimated models. One concern is whether or not the time series are stationary (Cromwell,

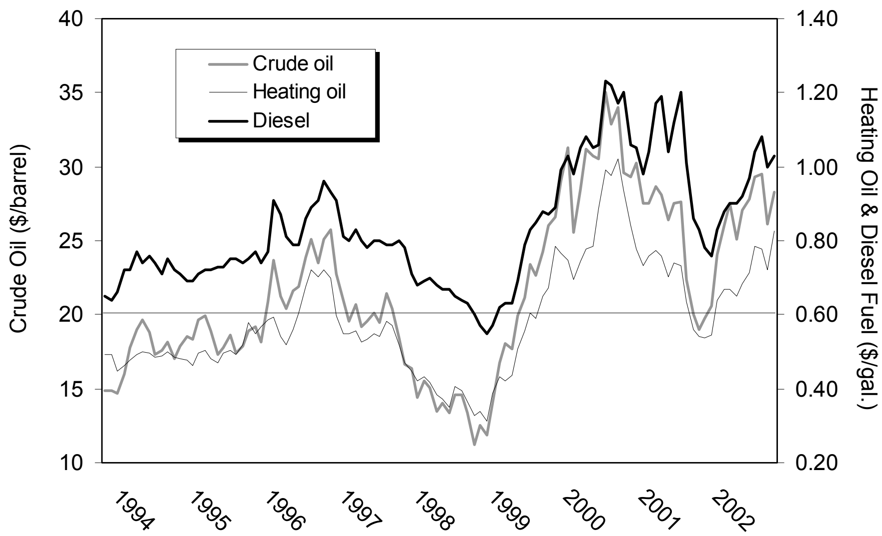

Figure 2. Monthly average NYMEX crude oil, NYMEX heating oil, and SW Kansas diesel fuel prices, 1994–2002

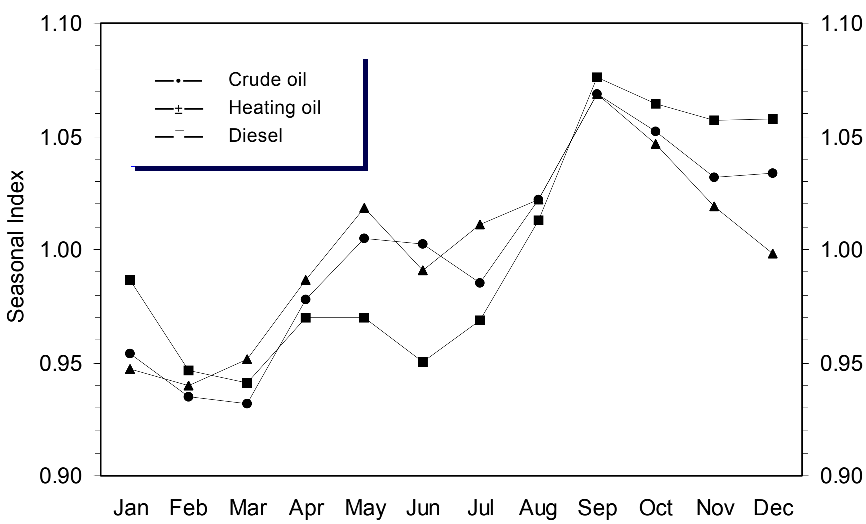

Figure 3. Seasonal price indices for NYMEX crude oil, NYMEX heating oil, and SW Kansas diesel fuel, 1994–2002

Labys, and Terraza, 1994). Visually examining the data series (figure 2) leads one to suspect these series are not stationary (i.e., a unit root exists). In addition to visually examining the data, each data series was tested for the presence of a unit root using the Phillips-Perron unit root tests (Phillips, 1987; Perron, 1988). In all cases, the null hypothesis of a unit root was not rejected, indicating the data are not stationary. Typically, if a unit root exists, data are differenced in order to make the series stationary. With all time series considered here, the presence of a unit root was rejected when estimating equations (2) and (3) with first-differenced data. However, a problem with estimating the models in differences is that results become more difficult to interpret, thereby undermining the objective of developing relatively simple forecasting models.

If two time series are cointegrated, then a regression based on the levels of the two variables is meaningful and standard *t*- and *F*-tests are valid, despite the two series being individually nonstationary (Engle and Granger, 1987). In other words, if the two series are nonstationary, but are "moving together" over time, a regression based on levels is appropriate. The different combinations of data series displayed in equations (2) and (3) (i.e., diesel/crude oil and diesel/heating oil) were tested for co-integration using the Engle-Granger test.[4] Both combinations of data series were found to be cointegrated. This result suggests equations (2) and (3) can be estimated in levels.

A second consideration with time-series data is the issue of autocorrelation. If autocorrelation exists and is not accounted for, parameters estimated with ordinary least squares are unbiased but not efficient, and the usual inference procedures are not appropriate (Greene, 1993). Autocorrelation was tested for, and errors from both models were found to be autocorrelated. Further analysis suggested errors were only correlated at one lag, and thus correcting for first-order autorcorrelation is sufficient.

Results

Equations (2) and (3) were estimated correcting for first-order autocorrelation with maximum likelihood.[5] Results are presented in table 2. In addition to the estimated parameters and associated standard errors, the autocorrelation term (*rho*), R^2, root mean squared error (RMSE), and the RMSE divided by the mean of the dependent variable are reported. Graff et al. (1997) reported this percentage error measure (RMSE/mean of dependent variable) as a means of comparing the relative risk of their models for different commodities. They calculated values for this measure of roughly 8% to 25% when regressing Kansas milo prices on corn futures prices, 10% to 14% for sunflower prices regressed on soybean oil prices, 2% to 7% for feeder

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[4] The Engle-Granger test is essentially the Dickey-Fuller test except that it is based on a regression of errors (first difference and lagged) as opposed to the series itself.

[5] Models were also estimated including monthly dummy variables and with the futures prices (crude oil and heating oil) lagged one month. Neither of these variations statistically improved the models based on in-sample statistics. Thus the more parsimonious models with contemporaneous prices are reported.

Table 2. Parameter Estimates for Southwest Kansas Diesel Fuel Price Models, 1994–2002 (dependent variable = *SW Kansas Diesel*, $/gallon)

	Parameter Estimate	
Independent Variable	Crude Oil Model	Heating Oil Model
Intercept	0.3128*	0.2839*
	(0.0392)	(0.0387)
NYMEX Crude Oil ($/barrel)	0.0243*	—
	(0.0018)	
NYMEX Heating Oil ($/gallon)	—	0.9369*
		(0.0627)
rho (autoregressive parameter)	0.6908*	0.6486*
	(0.0706)	(0.0743)
No. of Observations	108	108
R^2	0.9390	0.9359
RMSE	0.0409	0.0419
RMSE/Mean of Dep. Variable × 100	4.89%	5.01%

Notes: An asterisk (*) denotes statistical significance at the 0.05 level. Values in parentheses are standard errors.

cattle prices (steers and heifers of various weights) regressed on feeder cattle futures prices, and 9% to 15% for Chicago millfeed prices regressed on corn and soybean meal futures prices.

For both models, the intercept and slope coefficients were significantly different from zero, and variability in the futures prices explained most of the variability in cash diesel fuel prices (table 2). Comparing the RMSE of the two models with the standard deviation for diesel prices reported in table 1 reveals that using these models to predict diesel fuel prices would be superior to simply using a historical average as a prediction. Based on in-sample predictive ability, diesel fuel prices can be predicted slightly better using the crude oil futures market than with the heating oil market. However, the difference is quite small. The RMSE divided by the mean diesel price was 4.89% and 5.01% for the crude oil and heating oil models, respectively. These levels are comparable to or lower than most of the commodities examined by Graff et al. (1997), suggesting futures-based price forecasts for diesel prices have some merit.

It is important to note that unit root and cointegration tests, and estimating equations (2) and (3) while correcting for autocorrelation, were done solely to verify the above-made inferences. In the following section, we examine whether models estimated by regressing cash diesel fuel prices on crude oil futures prices can be used profitably in a real-time decision-making framework. Only crude oil was considered, as it was slightly better than heating oil (table 2), and because the crude oil futures contract has considerably more trading volume than the heating oil market.

Model Simulation for Decision Making

The results presented in table 2 provide evidence that producers and agribusinesses could estimate a model using crude oil futures prices to predict diesel fuel prices with a reasonable amount of accuracy. However, a logical question remains to be answered: Could this information be used in real time to make purchase decisions? To address this question, we analyzed several diesel purchase decision rules a producer might consider. The two base assumptions of the diesel purchasing scenarios were: (*a*) diesel fuel is needed in April, and (*b*) the producer is willing to purchase diesel fuel needed in April up to five months in advance (i.e., starting in November of the previous year).[6] The decision rule analyzed is characterized as follows:

$$(4)\quad \begin{array}{ll} \text{If:} & \textit{Predicted April Price}_t > \textit{Cash Price}_t \,\%\, \textit{Cost of Carry}_{t,April}, \\ \text{Then:} & \text{Purchase diesel at time } t; \\ \text{Else:} & \text{Reevaluate next month (i.e., } t \,\%\, 1), \end{array}$$

where *Predicted April Price* is a model-predicted price of diesel fuel for the month of April, *Cash Price* is the current cash price of diesel, *Cost of Carry* is the cost of "storing" diesel until April, and *t* represents the five pre-purchase months considered (November through March). *Cost of Carry* was calculated as:

$$(5)\quad \begin{array}{l} \textit{Cost of Carry}_{t,April} \;' \\ \textit{Cash Price}_t \times (1 \,\%\, \textit{Interest Rate}_t/12)^k \,\&\, \textit{Cash Price}_t, \end{array}$$

where *Interest Rate* is the prime interest rate (Federal Reserve Bank of St. Louis, 2003), *k* is the number of months from *t* until April, and all other variables are as previously defined.[7] In words, the decision rule is simply that a producer buys diesel this month if the current price plus interest cost is less than the predicted April price. If the predicted price is less, then the producer delays any purchases and reevaluates prices again next month. If predicted prices are continuously below the cash price plus interest costs, the producer simply purchases diesel in April.

Two variations of the model are considered, *single purchase* and *multiple purchases*. With the single-purchase scenario, the producer buys diesel at the first "buy signal" he receives beginning in November, and then this price is compared to the April price. Multiple purchases means a producer is willing to only purchase a

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[6] The choice of April was arbitrary and was selected simply because it coincides with the time frame when many producers would need diesel fuel for spring field work. Similar analyses could be conducted examining other months. Likewise, the choice of purchases five months in advance was considered because this would reflect the time period from post-harvest until spring field work the following year, and also because producers consider pre-purchasing inputs at that time of year for tax reasons.

[7] The physical cost of a storage tank has been excluded because it would require numerous assumptions about the size of the tank, cost, intensity of use, and useful life of the tank. Furthermore, if a producer already owns storage tanks, this is a fixed cost. Thus, cost savings associated with pre-purchasing diesel should be viewed as returns to storage tanks.

maximum amount in any month prior to April. For example, if a producer is reluctant to purchase more than 1/3 of his diesel needs in any one month prior to April, he would purchase 33.3% when the first “buy signal” is received, and then another 33.3% at the next signal, and so on until the producer is either 100% purchased or he reaches April, whichever comes first. In this case, the weighted average price paid of the multiple purchases is compared to the April price. If a producer is willing to purchase 100% in any one month, the multiple-purchase strategy collapses to the single-purchase strategy.

In order to maximize the number of years the purchasing decision rule [equation (4)] could be followed, several data assumptions were made. Because crude oil futures only began trading in May of 1983, there are limited data for out-of-sample analyses. Thus, it was assumed a producer is willing to estimate a regression model like equation (2) with only three years of data (36 observations). This allowed the first year of out-of-sample model predictions to occur for April 1987, giving a total of 16 years for the analysis (1987 through 2002).

However, another data problem is that the producer-level monthly cash prices for diesel in southwest Kansas were only available beginning in 1994. Therefore, prior years had to be estimated in order to evaluate the purchasing decision rule over the 16 years when futures-price-based models were available. Monthly prices for diesel in southwest Kansas from May 1983 through December 1993 were estimated with a regression model using the DSRTUUS and DSTXUUS price and tax series (U.S. Department of Energy/Energy Information Administration, 2003).[8]

The *Predicted April Price* in equation (4) comes from plugging the May futures price (nearby contract in April) into a regression equation of nearby crude oil futures and cash diesel prices [like equation (2)] that is estimated with ordinary least squares (OLS) using the most recent historical prices available (beginning with a minimum of 42 observations).[9] For example, in November of 1986, the *Predicted April Cash Price* is \$0.6734 = 0.34312 + 0.02152(\$15.35), where 0.34312 and 0.02152 are parameter estimates from the most recent 42 months (May 1983 through October 1986), and \$15.35 is the May crude oil futures price in the month of November. This process was repeated for each month moving forward, allowing the number of observations used in estimating the regression equation to increase each month.[10] There were a total of 80 models estimated (five months prior to November for 16 years) where each model was similar to equation (2). Model statistics of the 80 individual

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[8] Southwest Kansas diesel prices from January 1994 through December 2002 (108 observations) were regressed on national average diesel price excluding state and federal taxes (DSRTUUS minus DSTXUUS) and monthly dummy variables. The in-sample RMSE was 3.5¢ and the R^2 was 0.96. This estimated model and historical national average prices were then used to predict southwest Kansas prices for January 1986 through December 1993.

[9] Regression equations estimated for real-time price forecasts were estimated with OLS without correcting for autocorrelation. This was done because the models are simply being used for out-of-sample predictions (estimated betas are unbiased even if autocorrelation is present) and because this is a procedure producers or agribusinesses could easily duplicate in a spreadsheet.

[10] The final regression was in March of 2002, and was based on 226 observations (May 1983 through February 2002). Results were similar when analysis was done with arbitrarily capping the maximum number of observations used in regressions at 120 most recent months (10 years).

Table 3. Price Paid for SW Kansas Diesel Fuel Following Purchase Decision Rule versus April Spot Purchase, 1987–2002 ($/gallon)

Year / Description	April Purchase	Single Purchase [a]	Multiple Purchases (maximum per month prior to April) [b]				
			50%	33.3%	25%	20%	16.7%
1987	0.650	0.606	0.627	0.639	0.641	0.640	0.642
1988	0.675	0.655	0.665	0.668	0.670	0.671	0.672
1989	0.744	0.683	0.688	0.707	0.716	0.722	0.725
1990	0.747	0.746	0.746	0.746	0.747	0.747	0.747
1991	0.742	0.750	0.746	0.745	0.744	0.743	0.743
1992	0.732	0.709	0.706	0.715	0.719	0.722	0.723
1993	0.755	0.738	0.744	0.748	0.750	0.751	0.751
1994	0.720	0.660	0.653	0.675	0.687	0.693	0.698
1995	0.710	0.700	0.698	0.702	0.704	0.705	0.706
1996	0.910	0.910	0.910	0.910	0.910	0.910	0.910
1997	0.800	0.800	0.800	0.800	0.800	0.800	0.800
1998	0.690	0.690	0.690	0.690	0.690	0.690	0.690
1999	0.620	0.581	0.569	0.571	0.583	0.590	0.595
2000	0.980	0.980	0.980	0.980	0.980	0.980	0.980
2001	1.040	1.040	1.040	1.040	1.040	1.040	1.040
2002	0.880	0.766	0.800	0.826	0.840	0.848	0.853
Average	0.775	0.751	0.754	0.760	0.764	0.766	0.767
Minimum	0.620	0.581	0.569	0.571	0.583	0.590	0.595
Maximum	1.040	1.040	1.040	1.040	1.040	1.040	1.040
Std. Deviation	0.119	0.128	0.128	0.125	0.123	0.122	0.122
Cost Savings	base	0.024*	0.021*	0.015*	0.011*	0.009*	0.007*
p-Value [c]	base	0.011	0.009	0.010	0.010	0.009	0.009

Note: An asterisk (*) denotes statistical significance at the 0.05 level.

[a] Single purchase refers to 100% of diesel fuel being purchased in one month. This month is either the first "buy signal" from the model or April, whichever comes first.

[b] Multiple purchases are interpreted as follows: 50% means a producer pre-purchases 100% of diesel fuel over the first two months "buy signals" are received, 33.3% means a producer pre-purchases 100% of diesel fuel over the first three months "buy signals" are received, and so on. If there are not enough buy signals received to trigger 100% pre-purchases, then the remaining amount is purchased in April.

[c] The *p*-value is associated with a paired *t*-test of the means.

regressions are not reported to conserve space, but are available from the authors upon request. The RMSE of the 80 April cash price predictions was 7.4¢ per gallon.

Table 3 reports the prices paid for diesel following the purchase decision rule (single and multiple purchases) as well as April spot purchases. Basing diesel purchase decisions on regression-based predicted prices using the crude oil futures resulted in slight cost savings. Cost savings were largest for producers willing to purchase a higher percentage of their fuel needs prior to April. For example, the average cost savings for single purchases was 2.4¢ per gallon, but only 1.1¢ for producers who weren't willing to price more than 25% of their fuel in any one month. Based

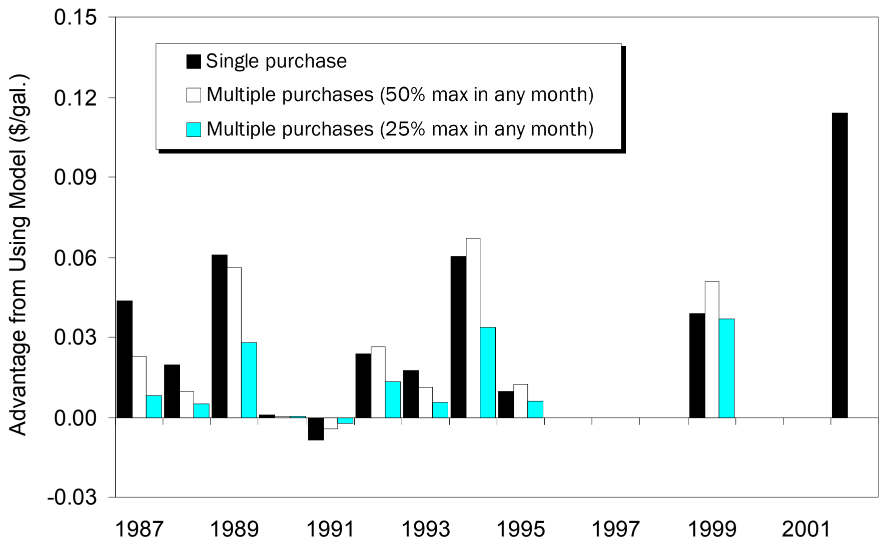

Figure 4. Diesel fuel purchase price comparison: Futures-based model decision price less April cash price, SW Kansas, 1987–2002

on a paired *t*-test, the cost savings of following the model-based decision rule were statistically different than zero. However, while they are statistically significant, it is important to note cost savings of this magnitude may not be economically significant.

Figure 4 shows the cost savings from following the purchase decision rule model for single purchases (i.e., 100% maximum in any one month) and multiple purchases with a maximum of 50% and 25% in any one month. Several results are apparent from this figure. First, it can be seen that in five years out of the 16, the model never provided a signal to purchase prior to April, and thus there were no cost savings. Second, as expected, the variability in savings is greater when fewer constraints are placed on the model (i.e., single purchases). The standard deviations in cost savings were 3.3¢, 2.3¢, 1.7¢, 1.3¢, 1.0¢, and 0.9¢ per gallon for 100% (single purchases), 50%, 33.3%, 25%, 20%, and 16.7% maximum monthly purchase strategies, respectively. Therefore, if a producer forces pre-purchase decisions to occur over multiple months, there is less risk relative to spot purchases in April (and less savings as well).

As a sensitivity analysis, the analysis was repeated using the November to March (four pricing months) and the November to May (six pricing months) time horizons. The average costs savings following the model-based decision were 3.1¢ and 1.6¢ per gallon for producers willing to purchase 100% and 25% of their fuel in any one month, respectively, for the November to May time period. However, for the November to March time period, there were no cost savings from following the model (i.e., the cost savings were equal to zero).

Summary and Conclusions

Agricultural producers and input suppliers regularly make management decisions based on forecasts. However, most publicly available forecasts are for outputs (e.g., grain and livestock). Research has shown that being in the lowest third of costs is both easier to accomplish and more profitable than being in the top third of prices received. Thus, it stands to reason that producers may benefit from focusing on crop input costs. Similarly, input suppliers could also benefit from a knowledge of methods to manage input and output price risks to lock in a margin. This does not mean they should try to "outguess" the market, but rather they should use what information they have readily available to them to make informed management decisions. The objective of this research was to estimate models based on futures markets that could be used to forecast diesel fuel prices. Futures-based models are appealing because they rely on the concept of efficient markets (i.e., futures markets capture all information).

Many producers and lenders predict input prices based on historical averages. The results of this research suggest diesel prices forecasted using the crude oil or heating oil futures market are reasonably accurate, and this approach is superior to using a historical average. Based on in-sample predictive ability, diesel prices were predicted slightly better using the crude oil futures market than the heating oil market. However, the difference was quite small.

Based on 16 years of out-of-sample price predictions, using futures-based price predictions for diesel to make purchasing decisions resulted in slight cost savings compared to spot market purchases. Cost savings were largest for producers willing to purchase a higher percentage of their fuel needs prior to April. The average cost savings for producers willing to price 100% of their fuel in a single month was 2.4¢ per gallon, but it was only 1.1¢ for producers who weren't willing to price more than 25% of their fuel in any one month. While these gains from following a model-based decision rule were quite small, they were positive, suggesting producers would not be worse off.

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