



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Forecasting and Hedging Crop Input Prices

Kevin C. Dhuyvetter

Martin Albright

and

Joseph L. Parcell*

*Paper presented at the NCR-134 Conference on Applied Commodity Price
Analysis, Forecasting, and Market Risk Management
St. Louis, Missouri, April 23-24, 2001*

Copyright 2001 by Kevin C. Dhuyvetter, Martin Albright, and Joseph L. Parcell. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

* The authors are associate professor (kdhuyvet@agecon.ksu.edu), Administrator of Kansas Farm Management Association (albright@agecon.ksu.edu), Department of Agricultural Economics Kansas State University, and assistant professor (parcellj@missouri.edu), Department of Agricultural Economics University of Missouri, respectively.

Forecasting and Hedging Crop Input Prices

Agricultural producers and input suppliers have to make management decisions based on forecasts all the time, however, most available forecasts are for outputs (e.g., grain and livestock). Research has shown that one of the most important determinants of relative profitability for producers is being a low-cost operator. Research has also shown that relatively simple forecasting models are often superior to more complex models. Thus, producers may benefit from having simple models for forecasting crop input costs. The objective of this research was to estimate models based on futures markets that could be used to forecast input prices, specifically, diesel fuel, natural gas, and anhydrous ammonia. Results suggest that diesel prices forecasted using the crude oil or heating oil futures market are reasonably accurate and that this approach may be superior to using an historical average. While diesel prices could be effectively cross hedged with the crude oil or heating oil futures market, the contracts represent relatively large quantities which may exceed individual producer's needs so cross hedging may only be practical for input suppliers. Likewise, producers using natural gas for irrigation can use the natural gas futures market to predict what their local cash prices will be. Anhydrous ammonia prices can be predicted using natural gas prices, however, because of a major structural change that occurred in the nitrogen fertilizer industry during the mid nineties these price forecasts are less reliable.

Key words: Forecasts, Cross hedging, Energy, Diesel, Natural gas, Anhydrous ammonia

Introduction

Profitability is simply the difference between revenue and expenses. For crop producers, revenue comes from crop sales, government payments, and insurance indemnity payments. Expenses are both direct production inputs (e.g., seed, fertilizer, chemicals) and fixed inputs (e.g., labor, management, and asset charges). Because the 1996 Farm Bill increased producers planting flexibility and decoupled government payments there has been an increased emphasis on risk management for producers. 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 (USDA). Thus, much of the recent focus pertaining to risk management has been on marketing and crop insurance strategies (e.g., Dhuyvetter and Kastens; Wisner, Blue, and Baldwin; Zulauf and Irwin).

If markets are efficient and returns cannot be significantly increased by following some routine marketing strategy, then it may be that producers should focus their management efforts in other areas. Nivens and Kastens found that managing for 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 that it was easier for producers to differentiate themselves from other producers with regards to cost compared to price. Thus, not only was cost control more profitable, but it was easier to do, or not to do, relative to other farmers. Therefore, it may be that producers will benefit from a better understanding of crop input prices to better manage their production input costs.

Energy prices, specifically crude oil and natural gas prices, increased significantly in 2000 compared to prices the previous ten years (Figure 1). Energy prices are correlated with the prices of many crop inputs, i.e., chemicals, fertilizers, and fuel and oil, due to the use of crude oil and natural gas as primary feedstocks in the production of these inputs. As crude oil and natural gas prices rose to decade highs in 2000, producers began asking what these higher energy prices would mean in terms of crop production input prices, specifically diesel, natural gas, and nitrogen fertilizer prices. Having price forecasts for these different crop inputs is useful for producers to make management decisions as they: 1) convey to their lenders an estimate of required operating capital requirements for the upcoming year; 2) determine optimal crop mix and input use, e.g., optimal fertilizer or irrigation amounts; and 3) make production decisions regarding management practices, e.g., level of tillage, dryland versus irrigation, harvest date. Another question some producers asked in the fall of 2000 was whether they should forward contract inputs for 2001 production needs.

The primary objective of this study is to examine historical relationships between diesel fuel prices and the crude oil and heating oil futures market as well as nitrogen fertilizer prices and the natural gas futures market to develop models that producers and input suppliers can use to use make real-time price forecasts. A second objective is to examine the effectiveness and accuracy of cross-hedging various crop inputs. A final objective is to simply identify historical prices and seasonal patterns for various crop inputs as this information is seldom reported publicly to producers.

Background

Forecasting models can be quite 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 relatively 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 as they make their production and purchasing decisions. Anderson and Mapp indicated that producers want simple, easy to use, decision rules, thus, the more complex a model becomes the less likely it will be used by producers. For example, structural models requiring ancillary forecasts of explanatory data are of little value to producers needing to make production decisions based on real-time input price forecasts with limited information available. Therefore, a forecasting model that producers can use in real-time should be relatively simple.

Kastens, Jones, and Schroeder compared various simple-to-construct forecasting methods and concluded that the deferred futures plus historical basis forecast method was the most accurate for most commodities considered. Furthermore, they indicated that more complex regression based models did not improve accuracy and the added sophistication of these models was not merited. Dhuyvetter and Kastens compared alternative methods of forecasting basis and they concluded that simple models (historical averages) were as accurate as more complex models. Thus, this provides evidence that 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. Furthermore, futures-based price forecasts are also appealing as they implicitly assume futures markets are efficient and thus represent all relevant information.

If the current futures market price reflects all information in past prices, then it is defined as being weak-form efficient (Fama). Tomek suggests that futures markets are weak-form efficient, implying that other publicly available price forecasts cannot outperform the futures market forecast. He concluded that futures prices can be viewed as forecasts and that structural or time-series econometric models cannot improve on the futures market forecast. With weak-form efficient markets 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 suggest that futures markets be used as a source of information rather than as a trading medium. Similarly, Brorsen and Irwin suggest 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.). Thus, assuming that crop input markets for fertilizer and fuel are also characterized by efficient markets, then it seems appropriate to encourage producers and input suppliers to use futures-based price forecasts for crop inputs to help them make their production and purchasing decisions.

If producers anticipate that 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. However, it has been documented that forward contracting is not costless, e.g., Brorsen, Coombs, and Anderson; Elam. Thus, producers may want to consider hedging the price of inputs rather than forward contracting, if this is a viable alternative. Graff et al. estimated cross-hedge relationships for numerous commodities and showed that the risk associated with cross hedging varied by commodity (e.g., light weight feeder heifers could be cross hedged with feeder cattle futures much more successfully, i.e., less risk, than grain sorghum with corn futures). In order to make informed decisions about either hedging or forward contracting, producers need to have some forecast as to where future price levels might be relative to current prices. Price forecasts for major crops and livestock are readily available from USDA, universities, market advisory services, farm magazines, etc. However, forecasts for crop inputs such as fertilizer, diesel, natural gas, etc. typically are much more

difficult to find.¹ A question that arises is, Where can producers and input suppliers get price forecasts for crop inputs, and can input prices be effectively cross-hedged to mitigate price risk?

Empirical Models

The concept of cross hedging refers to where the price of one cash commodity is hedged in the futures market of a different commodity (Graff et al.). Put another way, the concept of cross hedging simply uses information in one market (i.e., the futures market) to “lock in” or predict the price of a different commodity in another market (i.e., the cash market). Information pertaining to cross hedging (i.e., hedge ratio and cash quantity hedged) are found by estimating the following equation:

$$\text{Cash price} = \beta_0 + \beta_1 \text{Futures price} , \quad (1)$$

where β_0 represents the expected basis and β_1 is the hedge ratio. The cash quantity hedged is found by dividing the futures contract quantity by the hedge ratio, β_1 . Equation (1) is typically used to estimate the cross-hedge relationship between two commodities that are close substitutes, e.g., corn and milo (grain sorghum), 7-8 cwt steers and 6-7 cwt heifers. If the difference between the two commodities is not constant throughout the year, then it may be that monthly dummy variables should be added to the right hand side of (1) allowing the basis to vary seasonally.² Furthermore, while the cash and futures prices in equation (1) are typically contemporaneous it may be that a lag is justified to allow for time associated with processing in some cases depending on the specific commodities considered.

Given that the objective here is to estimate empirical models based on the futures market that can be used for forecasting the price of diesel, natural gas, and nitrogen fertilizer, the relationship demonstrated in equation (1) can be used. Futures contracts considered here are crude oil, heating oil, and natural gas — all 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 that the prices of these two commodities will move together. Furthermore, diesel fuel and heating oil are both derivatives of crude oil so the prices of all three of these commodities are expected to move together. The primary feedstock in the production of the major nitrogen fertilizer – anhydrous ammonia (NH₃) – is natural gas

¹ The Department of Energy provides a monthly U.S. average diesel price forecast, however, diesel price levels and seasonal patterns can vary between geographical locations. Thus, localized diesel price forecasts are warranted.

² Another way seasonality could be accounted for would be to estimate equation (1) for each individual contract month.

suggesting that the prices of anhydrous ammonia and natural gas will move together. Based on these expected relationships the following models are defined,

$$\text{Diesel price} = \beta_0 + \beta_1 \text{NYMEX crude oil} + \beta_{(2-12)} \text{MONTH} + \epsilon, \quad (2)$$

$$\text{Diesel price} = \beta_0 + \beta_1 \text{NYMEX heating oil} + \beta_{(2-12)} \text{MONTH} + \epsilon, \quad (3)$$

$$\text{Natural gas price} = \beta_0 + \beta_1 \text{NYMEX natural gas} + \beta_{(2-12)} \text{MONTH} + \epsilon, \quad (4)$$

$$\text{NH3 price} = \beta_0 + \beta_1 \text{Natural gas} + \beta_{(2-12)} \text{MONTH} + \epsilon, \quad (5)$$

where *Diesel price*, *Natural gas price*, and *NH3 price* represent producer level crop production input prices; *NYMEX crude oil*, *NYMEX heating oil*, and *NYMEX natural gas* represent futures market prices, *MONTH* is a binary variable for each month (July = default), ϵ represents an error term, and $\beta_0 - \beta_{12}$ represent parameters to estimate. Equations (2) and (3) are both considered to determine which futures contract – crude oil or heating oil – works better for hedging or predicting the price of diesel.³ Equation (4) is included to examine how well “local cash” prices for natural gas move with the futures market and thus would not be considered a cross hedge but rather a “straight” hedge. Monthly dummy variables have been added to all equations to allow for the basis (i.e., intercept) to vary seasonally.

From a producer’s perspective, equations (2) through (5) are appealing in that once they are estimated they provide a relatively easy way to forecast the prices for major crop inputs while relying on several key economic principles. These equations rely on the concept of cross hedging which is widely accepted and they also rely on 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 other commodities. Average monthly prices were collected for bulk delivered diesel in southwest Kansas, natural gas prices at two locations (southwest Kansas and Louisiana) and anhydrous ammonia (NH3) prices in the midwest U.S. In addition to the different cash prices, monthly average nearby futures prices for crude oil, heating oil, and natural gas were collected (Bridge). Futures contracts are traded for each month of the year for crude oil, heating oil, and natural gas. 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

³ 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 thus may be more effective and practical for predicting diesel prices.

expires in late December), the nearby in February is the March contract, and so on. Time periods for which prices were collected varied by commodity. Table 1 reports the summary statistics for the different prices series.

A continuous time series of monthly average diesel prices was obtained from a fuel supplier in southwest Kansas from January 1994 through December 2000 (Gerber).⁴ Monthly diesel prices averaged almost 80¢ per gallon over this time period and ranged from a low of 55¢ to a high of \$1.23 per gallon. Natural gas prices were collected from two cash markets – Henry Hub, Louisiana and southwest Kansas – from May 1990 through December 2000.⁵ Henry Hub Louisiana is the delivery point for futures contracts and represents the major cash market that industries (energy, fertilizer, and chemical) typically base prices off of. Because the Henry Hub natural gas price is used by the fertilizer industry, the price of anhydrous ammonia is considered to be a function of this price rather than the futures price (i.e., equation (5) uses Henry Hub natural gas rather than NYMEX).⁶ The price for southwest Kansas is an average price paid by irrigated crop producers in that region (Southwest Kansas Irrigator’s Association). Monthly average prices for anhydrous ammonia (NH₃) in the midwest U.S. were obtained from a private source (Blue, Johnson, and Associates) from January 1977 through December 2000. Given regulatory changes in the natural gas market beginning in January 1989, this analysis focuses on data from 1989 forward only.

Figures 2, 3, and 4 present the historical prices for the different commodities listed in Table 1. Examining the data visually helps identify if there are long-term trends in place and also gives somewhat of an indication if the models to be estimated might have some validity. Kansas diesel prices appear to fluctuate quite closely with both the heating oil and crude oil NYMEX futures prices (Figure 2). Figure 3 shows the natural gas prices for the NYMEX futures contract as well as the two cash price series. All three price series move together quite closely indicating the natural gas market is likely a national market. As an indication of why this market was so widely discussed in the media this past winter (e.g., Barrionuevo, Fialka, and Smith; Brown; Fisher), monthly average prices at the end of 2000 were more than double the previous high. Figure 4 shows anhydrous ammonia (NH₃) prices compared to the natural gas prices – the major cost in the production of NH₃. When natural gas prices are in the range of \$2.20/MMBtu, natural gas accounts for approximately 75% of the cost of producing NH₃, however, as the cost of natural gas increases it represents a larger share of the total cost

⁴ Kansas Agricultural Statistics reported monthly average diesel prices for Kansas prior to 1986. From 1986 through 1994 they reported prices on a quarterly basis and since 1995 they began reporting prices only once per year (April).

⁵ Cash prices were available prior to May 1990, however, natural gas did not trade on the NYMEX prior to this time thus prices are only reported for when futures prices were available.

⁶ Using the Henry Hub natural gas price in equation (5) rather than the NYMEX futures price also allows an additional 17 observations to be included when estimating the model.

of production of NH₃ (e.g. Phillips and Mathers, Doanes, Agriliance). Thus, assuming the nitrogen fertilizer industry is competitive (i.e., price = cost), we should be able to predict NH₃ prices reasonably well given natural gas prices. However, examining Figure 4 it is quite apparent that during the mid to late nineties the prices of NH₃ and natural gas did not follow each other very well for a period of about 36 months.

Figure 5 shows an estimated margin for NH₃ producers over this time period, where margin is defined as the price of NH₃ (\$/ton) less 35 times the cost of natural gas (\$/MMBtu) less \$62/ton for overhead and transportation.⁷ Margins oscillated around zero in the first half of the nineties and again at the end of the decade, however, for several years during the middle of the decade margins were extremely high. There were several fundamental factors that led to this period of what some might refer to as “excessive profits.” There was a shock to supply due to several ammonia production plants closing and the price of natural gas roughly tripled in Russia during the first half of 1995, sharply increasing the cost of imported nitrogen (Koch). From a demand perspective, during the mid nineties corn acreage was up and corn prices were at extremely high levels so crop input demand for nitrogen remained strong. The effect of the shock to supply and the continued strong demand was that for a period of time there was excess demand for nitrogen and NH₃ producers recognized short-run profits. However, because the nitrogen fertilizer industry is competitive these excess profits were bid back out of the market as the industry had time to adjust production. The relationship between NH₃ and natural gas prices during this high profit time period (approximately three years) was considerably different than the rest of the time period.

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 lack of information. Thus, individual producers may make incorrect decisions pertaining to forward pricing simply due to lack of information. In this case, simply knowing historical price patterns may be of use to producers. Figures 6, 7, and 8 show seasonal price indices for the different commodities of interest. Diesel, heating oil, and crude oil prices all follow a seasonal pattern that is characterized by low prices in the spring that gradually strengthen as the year progresses (Figure 6). Based on the seasonal indices, it appears that Kansas diesel prices may actually follow NYMEX crude oil futures prices slightly better than heating oil futures prices. Figures 7 and 8 show the 10-year average seasonal price indices for natural gas in southwest Kansas and NH₃ in the midwest, respectively, for the 1990-99 and 1991-00 time periods. While the two 10-year periods follow similar patterns, it can be seen that the impact of prices in late 2000 had a considerable effect on relatively long-term historical relationships.

⁷ It typically requires between 33 to 35 million Btu's (MMBtu) of natural gas to produce one ton of anhydrous ammonia (FertEcon; Koch; Myers; Phillips and Mathers).

Modeling Issues

There are several modeling issues that need to be addressed prior to the estimation of equations (2) through (5). With time series data one of the first concerns is whether or not the time series is stationary (Cromwell, Labys, and Terraza). Visually examining the data series (Figures 2, 3, and 4) leads one to suspect that these series are not stationary (i.e., a unit root exists). In addition to visually examining the data, all data series were tested for the presence of a unit root using the Phillips-Perron unit root tests (Phillips, Perron). 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) through (5) with first differenced data. However, a problem with estimating the models in differences is that results become more difficult to interpret which contradicts 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). In other words, if the two series are nonstationary, but are “moving together” over time, a regression based on levels is appropriate. Each of the different combinations of data series displayed in equations (2) through (5) were tested for cointegration using the Engle-Granger test.⁸ All combinations of data series were found to be cointegrated with the exception of anhydrous ammonia (NH₃) and natural gas, i.e., equation (5). Once again, this finding is somewhat expected simply based on a visual examination of the data. Based on this result, this suggests that equations (2) through (4) can be estimated in levels but this may not be appropriate for equation (5).

Another consideration is whether or not the time period of high margins in the nitrogen fertilizer industry should be accounted for in equation (5). Because this time period was likely the result of fundamental shocks to the industry, it seems plausible that the relationship between NH₃ and natural gas prices might differ between “high margin” times and more “normal” time periods. Supply and demand information should be included in the model to account for fundamental shocks, however, a dummy variable for time periods when margins are high is a feasible proxy variable.⁹ Based on this, equation (5) was modified to allow the intercept and slope to vary when margins are high. Margins were defined to be high whenever

⁸ 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.

⁹ This fix for high margin time periods is somewhat ad hoc because recognizing when margins will be “high” in real-time so as to account for them in a forecast is difficult. However, it is equally difficult to predict how fundamental factors will change in real-time and thus the dummy variable approach seems reasonable. The inclusion of a dummy variable is primarily done such that the estimated coefficients will be less biased for “normal” time periods.

they exceeded \$46.10/ton which was determined using the criteria of minimizing the sum of the squared errors. The revised model for anhydrous ammonia prices is

$$NH_3 \text{ price} = \beta_0 + \beta_1 \text{Natural gas} + \beta_2 \text{Margin} + \beta_3 \text{MargGas} + \beta_{(4-14)} \text{Month} + \epsilon, \quad (5a)$$

where *Margin* is a binary variable equal to one if margin is greater than \$46.10/ton and equal to zero otherwise, *MargGas* is an interaction between the margin binary variable and natural gas price, and all other variables are as previously defined. Based on the Engle-Granger test NH₃ and natural gas prices were found not to be cointegrated and thus estimating equation (5a) in levels may not be appropriate. Therefore, this model was estimated in both levels and first differences with all variables being first differences except the monthly dummy variables.

A final issue to consider with time series data is that 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). Autocorrelation was tested for using the Durbin-Watson statistic calculated from estimating equations (2) through (5a) using ordinary least squares. Based on the Durbin-Watson statistic, errors from all four models were found to be autocorrelated. Further analysis suggested that in most all cases errors were only correlated at one lag and thus correcting for first order autocorrelation is sufficient. It is important to remember that the objective here is to estimate models that can be used to forecast input prices 6 to 12 months out so the existence of autocorrelation is probably not a major concern.

Results

Equations (2) through (5a) were estimated correcting for first order autocorrelation with maximum likelihood. Results of the diesel price models are presented in table 2, natural gas price models in table 3, and the anhydrous ammonia price models in table 4. In addition to the estimated parameters and associated standard errors, root mean square error (RMSE) and the RMSE divided by the mean of the dependent variables are reported. Graff et al. reported this percent error measure (RMSE / mean of dependent variable) as a means of comparing the relative risk of their models for different commodities. They reported values for this measure of roughly 8 to 25 percent for cross hedging Kansas milo prices with the corn futures market, 10 to 14 percent for cross hedging sunflowers in the soybean oil market, 2 to 7 percent for cross hedging feeder cattle (steers and heifers of various weights) in the feeder cattle market, and 9 to 15 percent for Chicago millfeed cross hedged in the corn and soybean meal futures markets.

In the two diesel models, the intercept and slope coefficients were significantly different from zero but the majority of the monthly dummy variables were not statistically significant (Table 2). The lack of significance on the seasonal variables is not surprising given that futures contracts exist for every month of the year. However, the signs and magnitudes of the

monthly variables do vary somewhat between the crude oil and heating oil models confirming the slightly different seasonal patterns displayed in Figure 6. Comparing the RMSE of the two models with the standard deviation for diesel prices reported in Table 1 indicates that using these models to predict diesel prices would be superior to simply using an historical average as a prediction. Based on in-sample predictive ability, diesel prices can be predicted slightly better using the crude oil futures market than the heating oil market. The RMSE divided by the mean diesel price was 4.77% and 5.61% for the crude oil and heating oil models, respectively. These levels are comparable or lower than most of the commodities examined by Graff et al. suggesting that futures-based price forecasts for diesel prices have some merit. Dividing the estimated coefficients on crude oil (0.0242) and heating oil (0.8767) by the quantities in the respective futures contracts (1,000 barrels for crude oil and 42,000 gallons for heating oil) indicate that the price of 41,322 and 47,907 gallons of diesel would be hedged by trading one contract of crude oil and heating oil, respectively. Thus, while the crude oil or heating futures markets may be effective for cross hedging diesel prices, the size of the contracts may represent larger quantities than the needs of most individual producers. However, input suppliers may be able to effectively cross hedge diesel as these quantities are probably not an issue for them.

The estimated models for the two different natural gas price series confirm that prices are national in scope but that slight differences exist (Table 3). The intercept is not statistically different from zero and the futures market coefficient is almost identical to one for Henry Hub natural gas prices. This is not surprising given that Henry Hub is the delivery point for the futures market. However, several of the monthly variables were significant indicating that there is some seasonality in basis. Natural gas prices in southwest Kansas are lower than the futures market (i.e., intercept is negative indicating a negative basis) and they respond slightly less to changes in the futures market compared to Henry Hub prices. Additionally, while most of the monthly dummy variables are not statistically significant, the seasonal patterns for the different price series vary slightly. From a forecast accuracy perspective, prices could be predicted (in-sample) similarly. The RMSE / mean price of 5.43% and 5.48% for Henry Hub and southwest Kansas, respectively, is lower than most of those reported by Graff et al. However, for a “straight hedge” of 700-800 pound feeder steers they reported values between 1.28% and 2.82% indicating this natural gas “straight hedge” involves slightly more risk than some other commodities. Even though the risk associated with price forecasts from these models may be higher than some commodities, futures-based price forecasts may still be superior to the use of historical averages (i.e., RMSE is less than standard deviation of price).

The anhydrous ammonia (NH₃) model (equation 5a) was estimated in both levels and first differences. Based on the model estimated in levels, NH₃ prices increase by \$32.30/ton for every \$1 change in the price of natural gas during “normal” time periods, where normal is defined as being when margins are less than \$46.10/ton. During high margin time periods, the price of NH₃ is slightly negatively related to natural gas prices. Seasonally, NH₃ prices are higher in the spring (relative to July) which is consistent when the greatest demand for nitrogen fertilizer exists. The RMSE / mean price value of 6.98% suggests that NH₃ prices can be

predicted using the futures market with a reasonable amount of accuracy. However, it is important to remember that the dummy variable that was included is difficult to predict in real time and thus forecasts will be conditional on that assumption. From a cross hedge perspective, one natural gas contract (10,000 MMBtu) would effectively hedge 310 tons of NH₃ – assuming margins are “normal.” While the results from this estimated model seem reasonable, i.e., the coefficient on natural gas of 32.3 is close to the conversion factor of 33 to 35 (see footnote 5), they may simply be spurious results. The results of the model fit in levels were somewhat fragile when different time periods were considered especially when corrected for first order autocorrelation. Given the relatively short time period along with a major structural change occurring for about 25 percent of the months, it may be that a more complex model is required. Thus, while the results from the estimated model seems reasonable, they should be viewed and used with caution.

Because both price series considered here (natural gas and NH₃) are nonstationary and they are not cointegrated which suggests the model should be fit in differences rather than levels. However, the model fit in differences gives what appear to be nonsensical results. The estimated parameter for natural gas prices in the first differences model is \$3.33/ton change in the price of NH₃ given a \$1 change in the price of natural gas which is difficult to explain. Estimating equation (5a) in differences was based on tests for unit roots which are not without their problems (Greene). Furthermore, as Hendry and Mizon point out there are situations in which differencing can cause problems as serious as those it aims to solve. Based on the results here, it appears the model estimated in levels is more appropriate than the model estimated in first differences.

Summary and Conclusions

Agricultural producers and input suppliers have to make management decisions based on forecasts all the time, however, most 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 do 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 (such as cooperatives) could also benefit from understanding methods to manage input and output price risks to lock in a margin. This does not mean they should try to “out guess” 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 input prices, specifically, diesel fuel, natural gas, and anhydrous ammonia. Futures-based models are appealing in that they rely on the concept of efficient markets (i.e., futures markets capture all information) and cross hedging (i.e., the relationship of prices in two different markets). Furthermore, these models rely on information that is readily available to producers.

Many producers and lenders predict input prices based on historical averages. The results of this research suggest that diesel prices forecasted using the crude oil or heating oil

futures market are reasonably accurate and that this approach may be superior to using an historical average. Likewise, producers using natural gas for irrigation can use the natural gas futures market to predict what their local cash prices will be. Anhydrous ammonia prices can be predicted using natural gas prices, however, because of a major structural change that occurred in the nitrogen fertilizer industry during the mid nineties these price forecasts are less reliable.

There are several issues that need to be considered for future work on this area. In this research all predictive accuracy measures were based on in-sample forecasts. A better test of the models estimated here would be to evaluate them based on out-of-sample forecasts. Additionally, the results presented in this paper pertaining to anhydrous ammonia prices are somewhat fragile. Therefore, it is apparent that additional work is required to identify and explain is going on in that market. In that sense, the results presented in this paper pertaining to anhydrous ammonia should be viewed as work in progress rather than as the final explanation for this market.

References

- Agrilience. "Crop Nutrients Bulletin – Questions and Answers About Natural Gas Costs Fueling Nitrogen Prices." January 22, 2001. Agrilience, LLC. P.O. Box 7305, Kansas City, MO 64116.
- Anderson, K.B. and H.P. Mapp. "Risk Management Programs in Extension." *Journal of Agricultural and Resource Economics*, 21(1996):31-38.
- Barrionuevo, A., J.J. Fialka, and R. Smith. "Incentives to Burn – How Federal Policies, Industry Shifts Created a Natural-Gas Crunch." *Wall Street Journal*, January 3, 2001.
- Blue, Johnson, and Associates, Menlo Park, CA.
- Bridge Financial Data Center (CD-ROM). Bridge Financial, 20 South Wacker Drive, Suite 1810, Chicago, Illinois 60606-7404.
- Brorsen, W.B., J. Coombs, and K. Anderson. "The Cost of Forward Contracting Wheat." *Agribusiness*, 11(1995):349-354.
- Brorsen, W.B. and S.H. Irwin. "Improving the Relevance of Research on Price Forecasting and Marketing Strategies." *Agricultural and Resource Economics Review*, (1996):68-75.
- Brown, S.P.A. "Do Rising Oil Prices Threaten Economic Prosperity." *Southwest Economy*, Federal Reserve Board of Dallas, 6(November/December, 2000):1-5.
- Cromwell, J.B., W.C. Labys, and M. Terraza. 1994. *Univariate Tests for Time Series Models*, Sage University Paper series on Quantitative Applications in the Social Sciences, series no. 07-099. Thousand Oaks, CA: Sage.
- Dhuyvetter, K.C. and T.L. Kastens. "Linkages Between Crop Insurance and Pre-Harvest Hedging." *Journal of Agriculture and Applied Economics*, 31(1,1999):41-56.
- Dhuyvetter, K.C. and T.L. Kastens. "Forecasting Crop Basis: Practical Alternatives." NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Ed. T.C. Schroeder, Manhattan, Kansas: Kansas State University, Department of Agricultural Economics, 1998, pp. 49-67.
- Doanes Agricultural Report. "Energy Prices Will Affect Production Cost." Vol. 64, No. 1-6, January 5, 2001.

- Elam, E. "Cash Forward Contracting Versus Hedging of Fed Cattle, and the Impact of Cash Contracting on Cash Prices." *Journal of Agricultural and Resource Economics*, 17(1992):205-217.
- Engle, R.F. and C.W.J. Granger. "Co-integration and Error Correction: Representation, Estimation and Testing." *Econometrica*, 55(1987):251-276.
- Fama, E. "Efficient Capital Markets: A Review of Theory and Empirical Works." *Journal of Finance*, 25(1970):383-417.
- FertEcon. "A Monthly Review of Outlook for the International Ammonia Market." FertEcon Ammonia Futures, industry newsletter, September, 2000.
- Fisher, D. "The Gas Trap." *Forbes Magazine*, pp. 98-99, January 21, 2001.
- Gerber Oil Inc., Charleston, KS.
- Graff, J., T. Schroeder, R. Jones, and K. Dhuyvetter. 1997. "Cross Hedging Agricultural Commodities." *Kansas State Univ. Coop. Ext. Serv. Bull. MF-2284*.
- Greene, W.R. *Econometric Analysis*, 2nd ed. Englewood Cliffs, NJ: Prentice Hall, 1993.
- Hendry, D.F. and G.E. Mizon. "Serial Correlation as a Convenient Simplification, Not a Nuisance: A Comment on a Study of the Demand for Money by the Bank of England." *The Economic Journal*, 88(1978):549-563.
- Kastens, T.L., R. Jones, and T.C. Schroeder. "Futures-Based Price Forecasts for Agricultural Producers and Businesses." *Journal of Agricultural and Resource Economics*, 23(1,1998):294-307.
- Koch Industries, Wichita, KS. Personal communication, November 2000.
- Myers, G. "The Next Energy Crisis?" *Dealer Progress Magazine*, p. 16, Sept/Oct, 2000.
- Nivens, H. and T. Kastens. "Payoffs to Farm Management: How Important is Grain Marketing?" NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Ed. T.C. Schroeder, Manhattan, Kansas: Kansas State University, Department of Agricultural Economics, 1999, pp. 289-302.
- Perron, P. "Trends and Random Walks in Macroeconomic Time Series." *Journal of Economic Dynamics and Control*, 12(1988):297-332.

- Phillips, P.C.B., "Time Series Regression with a Unit Root." *Econometrica*, 55(1987):277-301.
- Phillips, R. and K. Mathers. "Fertilizer and Natural Gas." The Fertilizer Institute briefing paper, February 2001. [Http://www.tfi.org/indexarchive1.asp](http://www.tfi.org/indexarchive1.asp)
- Schroeder, T.C., J.L. Parcell, T.L. Kastens, and K.C. Dhuyvetter. "Perceptions of Marketing Strategies: Producers vs. Extension Economists." *Journal of Agriculture and Resource Economics*. 23(1,1998):279-293.
- Southwest Kansas Irrigator's Association, Ulysses, KS.
- Tomek, W.G. "Commodity Futures Prices as Forecasts." *Review of Agricultural Economics*, Vol. 19, No. 1, Spring/Summer 1997. p. 23-44.
- United States Department of Agriculture, Secretary's memorandum number SM 1010-2. [Http://www.usda.gov:80/ocio/directives/SM/SM1010-2.html](http://www.usda.gov:80/ocio/directives/SM/SM1010-2.html).
- Wisner, R.N., E.N. Blue and E.D. Baldwin. "Can Pre-harvest Marketing Strategies Increase Net Returns for Corn and Soybean Growers?" *NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, Ed. B.W. Brorson, Stillwater, Oklahoma: Oklahoma State University, Department of Agricultural Economics, 1997, pp. 26-41.
- Zulauf, C.R. and S.H. Irwin. "Market Efficiency and Marketing to Enhance Income of Crop Producers." *NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management*, Ed. B.W. Brorson, Stillwater, Oklahoma: Oklahoma State University, Department of Agricultural Economics, 1997, pp. 1-25.

Table 1. Summary Statistics for Variables Used in Estimation

Variable ^a	N ^b	Mean	Std Dev	Minimum	Maximum
<i>NYcrude</i>	84	20.2906	5.2871	11.2100	35.0000
<i>NYheat</i>	84	0.5575	0.1536	0.3120	1.0200
<i>KSdiesel</i>	84	0.7942	0.1487	0.5500	1.2300
<i>NYgas</i>	128	2.2483	0.9629	1.1580	8.8190
<i>HHgas</i>	128	2.2389	0.9618	1.2600	8.9500
<i>KSgas</i>	128	1.9112	0.9353	0.9300	8.1150
<i>NH3</i>	144	165.7113	44.7292	101.2500	273.7500
<i>HHgas_(t-1)</i>	144	2.1316	0.7285	1.2600	5.5380

^a *NYcrude* = NYMEX nearby crude oil futures price (\$/barrel), *NYheat* = NYMEX nearby heating oil futures price (\$/gallon), *KSdiesel* = Southwest, KS bulk delivered diesel price (\$/gallon), *NYgas* = NYMEX nearby natural gas futures price (\$/MMBtu), *HHgas* = Henry Hub, LA natural gas price (\$/MMBtu), *KSgas* = Southwest, KS natural gas price (\$/MMBtu) — *NH3* = Midwest U.S. anhydrous ammonia price (\$/ton), *HHgas(t-1)* = Henry Hub, LA natural gas price lagged one month (\$/MMBtu).

^b N = 84 represents January 1994 through December 2000, N = 128 represents May 1990 through December 2000, N = 144 represents January 1989 through December 2000.

Table 2. Parameter Estimates for Southwest Kansas Diesel Price Models [equations (2) and (3)].^a

Dependent variable	SW Kansas diesel, \$/gallon	SW Kansas diesel, \$/gallon
Independent variable	Parameter Estimate	Parameter Estimate
<i>Intercept</i>	0.2844* (0.0365)	0.3118* (0.0325)
<i>NYMEX crude oil, \$/barrel</i>	0.0242* (0.0016)	--- ---
<i>NYMEX heating oil, \$/gallon</i>	--- ---	0.8767* (0.0504)
<i>January</i>	0.0225 (0.0236)	-0.0443** (0.0258)
<i>February</i>	0.0132 (0.0237)	-0.0219 (0.0257)
<i>March</i>	-0.0025 (0.0232)	-0.0174 (0.0256)
<i>April</i>	0.0196 (0.0222)	0.0053 (0.0251)
<i>May</i>	0.0168 (0.0202)	0.0176 (0.0238)
<i>June</i>	0.0165 (0.0162)	0.0197 (0.0202)
<i>August</i>	0.0181 (0.0162)	-0.0048 (0.0203)
<i>September</i>	0.0259 (0.0203)	-0.0023 (0.0241)
<i>October</i>	0.0285 (0.0222)	-0.0083 (0.0254)
<i>November</i>	0.0269 (0.0232)	-0.0158 (0.0259)
<i>December</i>	0.0560* (0.0234)	-0.0016 (0.0258)
<i>Rho</i>	0.5669* (0.0985)	0.3883* (0.1101)
<i>Observations</i>	84	84
<i>RMSE</i>	0.0379	0.0446
<i>RMSE / Mean of dep var x 100, %</i>	4.77	5.61

^a Significance at the 0.05 and 0.10 levels denoted by * and **, respectively. Standard errors are in parentheses.

Table 3. Parameter Estimates for Natural Gas Models [equation (4)].^a

Dependent variable	HH natural gas, \$/MMBtu ^b	KS natural gas, \$/MMBtu ^b
Independent variable	Parameter Estimate	Parameter Estimate
<i>Intercept</i>	-0.0451 (0.0549)	-0.2256* (0.0496)
<i>NYMEX natural gas, \$/MMBtu</i>	1.0034* (0.0173)	0.9611* (0.0158)
<i>January</i>	0.2340* (0.0588)	0.0553 (0.0521)
<i>February</i>	0.1535* (0.0587)	0.0306 (0.0520)
<i>March</i>	0.1128** (0.0579)	0.0403 (0.0510)
<i>April</i>	0.0027 (0.0552)	-0.0275 (0.0482)
<i>May</i>	0.0262 (0.0516)	-0.0418 (0.0445)
<i>June</i>	0.0124 (0.0427)	-0.0668** (0.0361)
<i>August</i>	0.0121 (0.0427)	0.0437 (0.0361)
<i>September</i>	-0.0290 (0.0517)	-0.0259 (0.0446)
<i>October</i>	-0.0723 (0.0557)	-0.1097* (0.0487)
<i>November</i>	-0.1085** (0.0576)	-0.1259* (0.0508)
<i>December</i>	0.0300 (0.0590)	-0.0705 (0.0523)
<i>Rho</i>	0.4593* (0.0828)	0.5185* (0.0797)
<i>Observations</i>	128	128
<i>RMSE</i>	0.1210	0.1044
<i>RMSE / Mean of dep var x 100, %</i>	5.41	5.46

^a Significance at the 0.05 and 0.10 levels denoted by * and **, respectively. Standard errors are in parentheses.

^b HH natural gas = Henry Hub, La and KS natural gas = Southwest Kansas.

Table 4. Parameter Estimates for Anhydrous Ammonia (NH3) Model [equation (5a)].^a

Dependent variable	NH3, \$/ton ^b	$\hat{\Gamma}$ NH3, \$/ton ^c
Independent variable	Parameter Estimate	Parameter Estimate
<i>Intercept</i>	68.2558* (7.6557)	-4.0804** (2.2107)
<i>HH natural gas, \$/MMBtu^b</i>	32.2988* (2.8499)	3.4997 (2.4311)
<i>Margin dummy^b</i>	136.6400* (13.1244)	3.6277 (8.9017)
<i>HH gas x Margin, \$/MMBtu^b</i>	-38.0847* (5.3663)	-1.2423 (3.1402)
<i>January</i>	18.7591* (5.7158)	11.3903* (3.1630)
<i>February</i>	24.2931* (5.6599)	10.1994* (3.1123)
<i>March</i>	28.6903* (5.4905)	7.1024* (3.1145)
<i>April</i>	31.8196* (5.2419)	5.6917** (2.9982)
<i>May</i>	17.3257* (4.7182)	-3.3092 (2.8298)
<i>June</i>	5.0116 (3.7275)	-6.6058* (2.3336)
<i>August</i>	3.7758 (3.7468)	3.7954 (2.3581)
<i>September</i>	6.8057 (4.7243)	8.4668* (2.8005)
<i>October</i>	5.5871 (5.2168)	9.5910* (3.0015)
<i>November</i>	7.7227 (5.5209)	6.5952* (3.0734)
<i>December</i>	8.2788 (5.6497)	4.7509 (3.0922)
<i>Rho</i>	0.6032* (0.0705)	0.4411* (0.0796)
<i>Observations</i>	144	144
<i>RMSE</i>	11.5588	6.8598
<i>RMSE / Mean of dep var x 100, %</i>	6.98	---

^a Significance at the 0.05 and 0.10 levels denoted by * and **, respectively. Standard errors are in parentheses.

^b NH3 = Anhydrous ammonia price, midwest U.S.; *HH natural gas* = Natural gas price at Henry Hub, La lagged one month; *Margin dummy* = binary variable equal to one if margin > 46.1, zero otherwise; *HH gas x margin* = interaction between Henry Hub natural gas and the margin dummy.

^c $\hat{\Gamma}$ NH3 = First differenced anhydrous ammonia price, *HH natural gas*, *Margin dummy*, *HH gas x margin* are also first differences for this model.

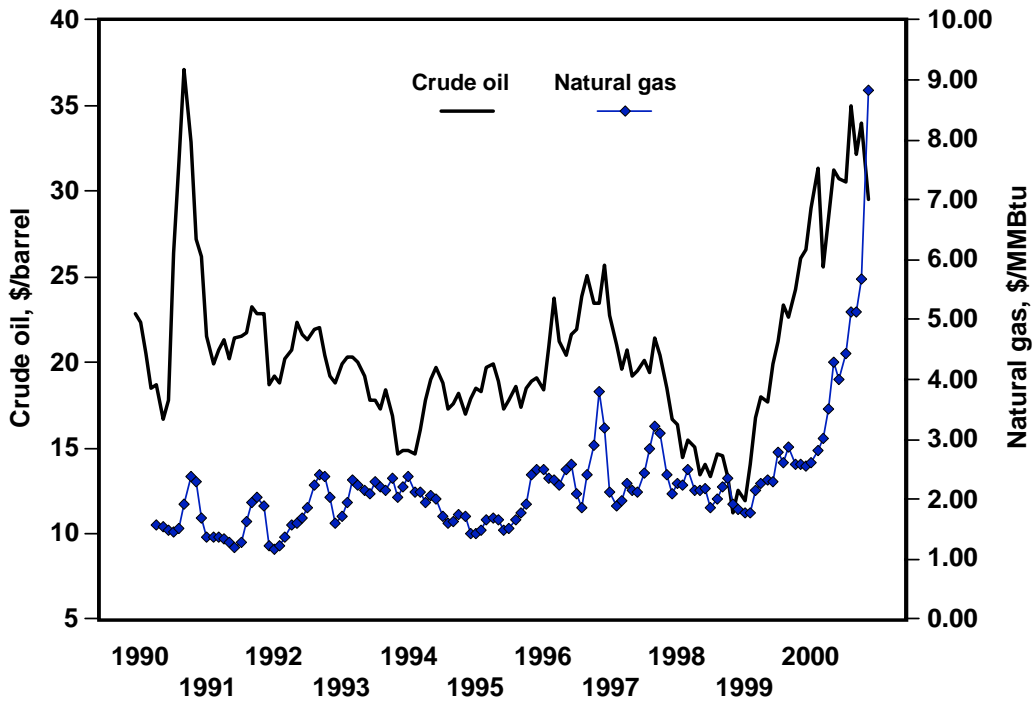


Figure 1. Monthly average crude oil and natural gas NYMEX nearby futures prices.

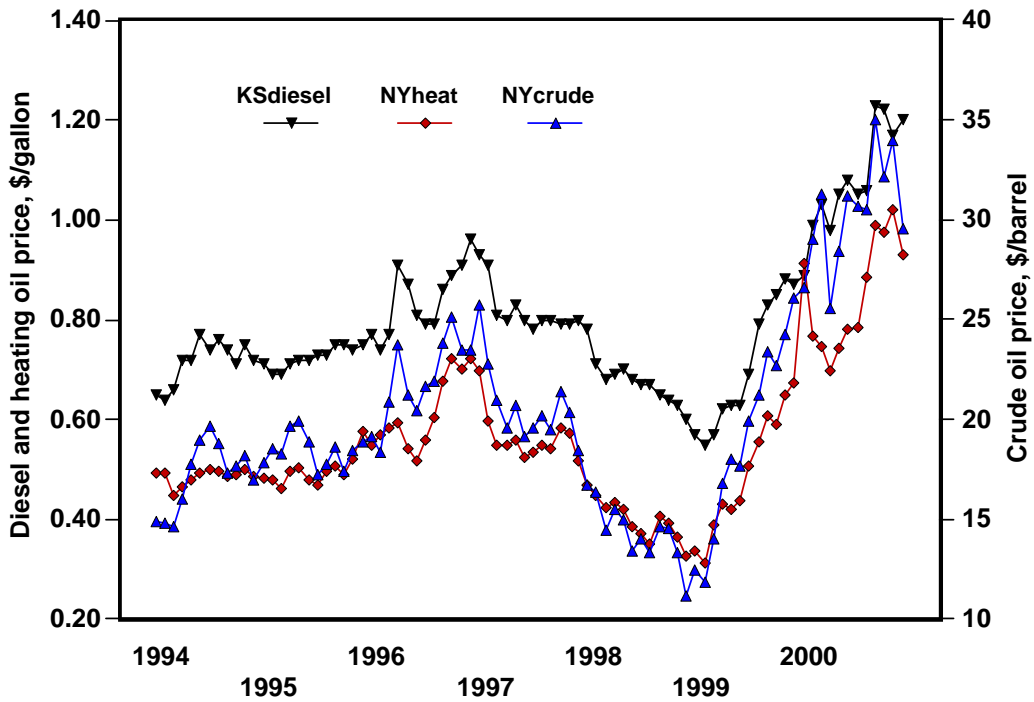


Figure 2. Monthly average diesel, heating oil, and crude oil prices.

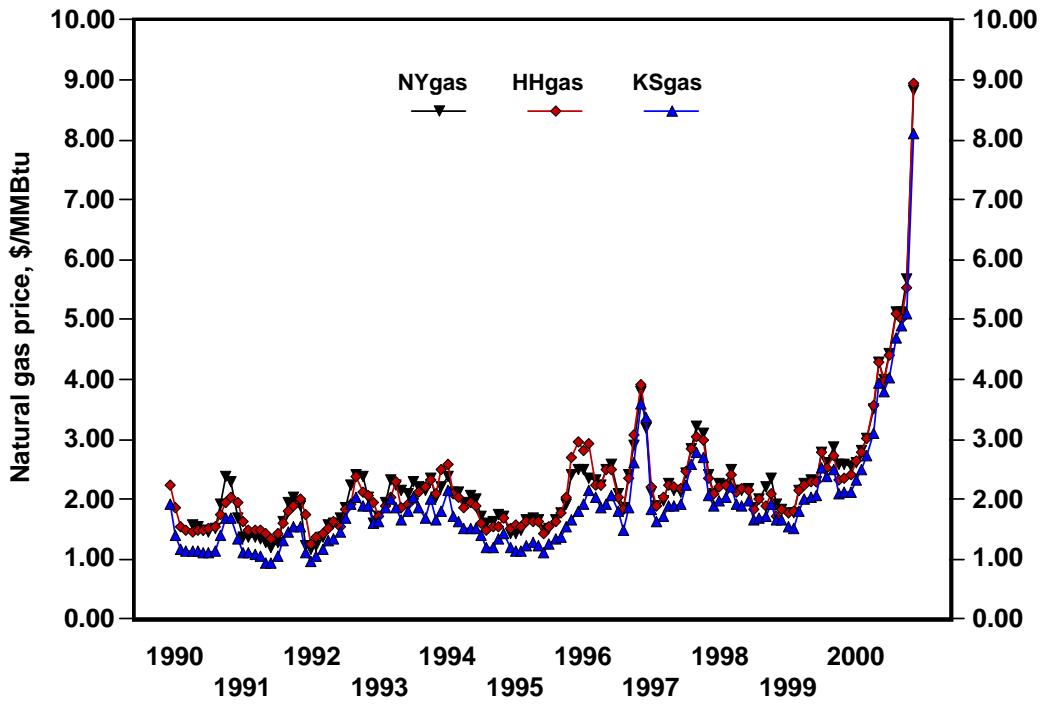


Figure 3. Monthly average natural gas prices.

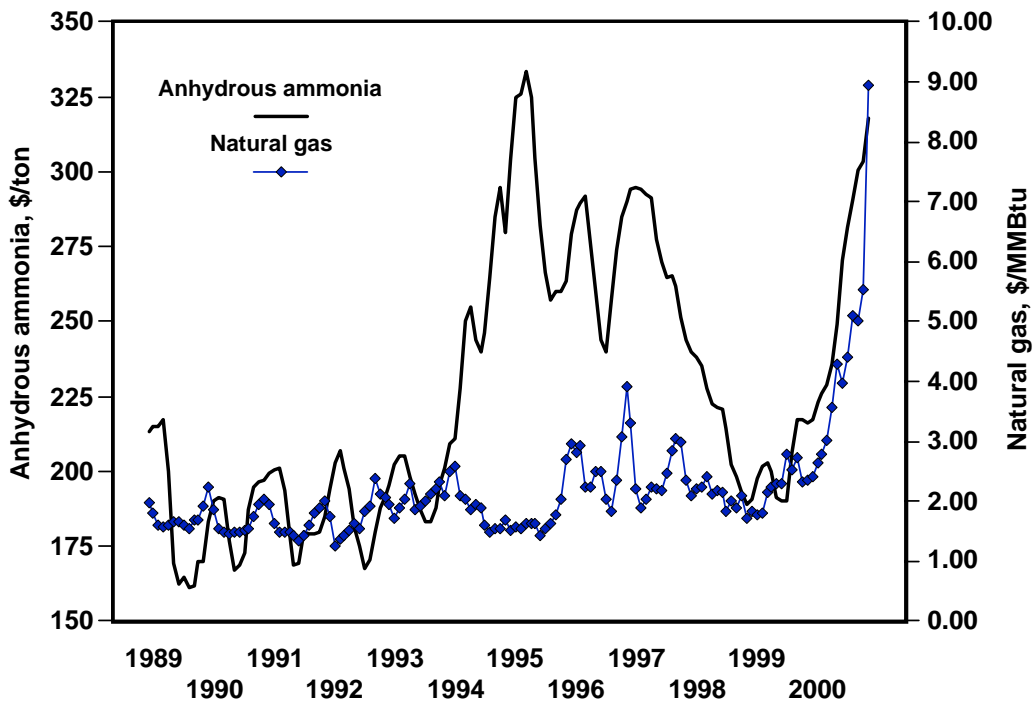


Figure 4. Monthly average anhydrous ammonia and natural gas prices.

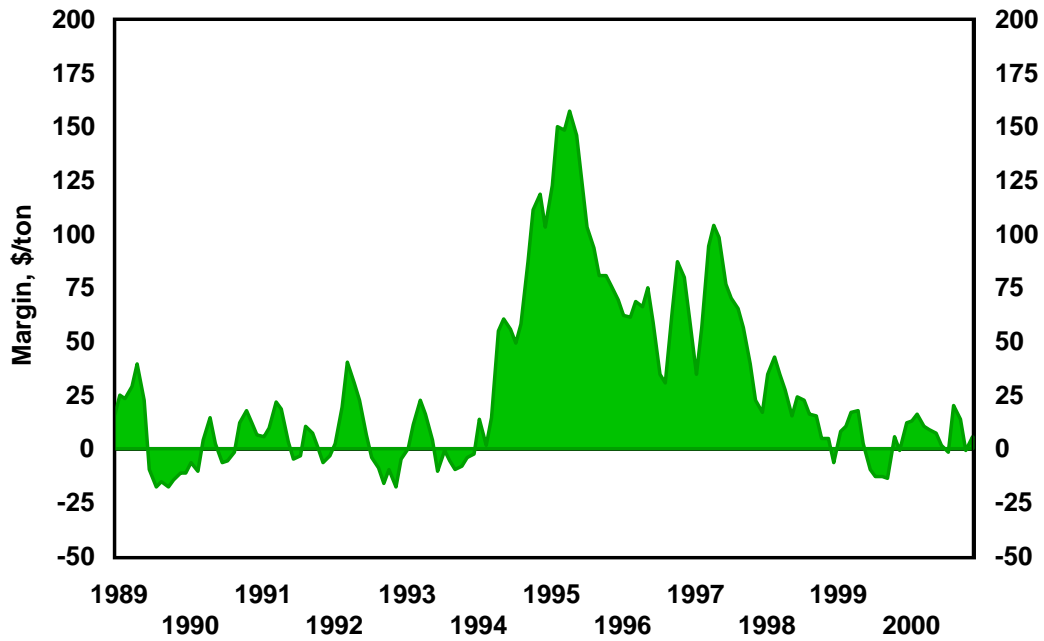


Figure 5. Estimated margin for anhydrous ammonia (NH₃) production.

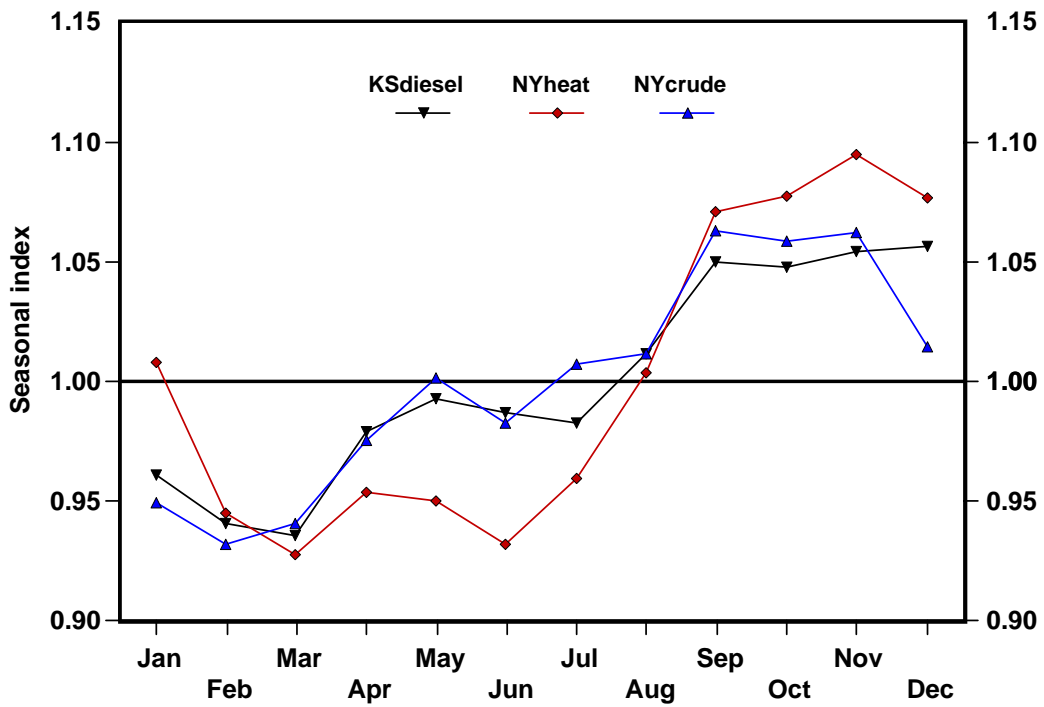


Figure 6. Seasonal price indices for diesel, heating oil, and crude oil, 1994-2000.

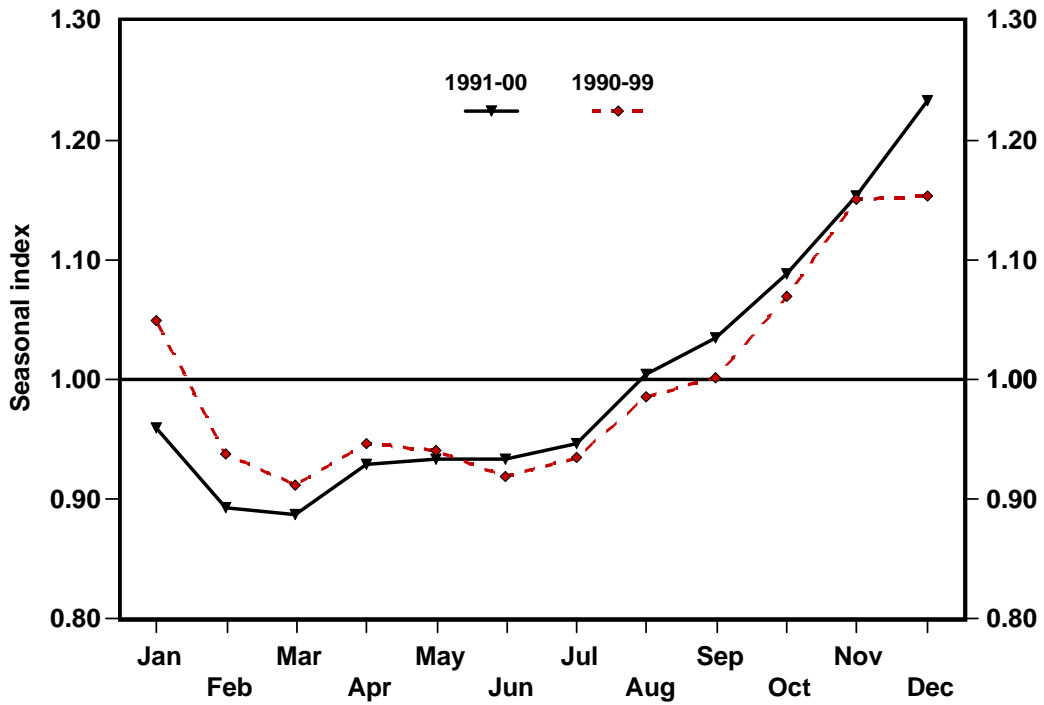


Figure 7. Seasonal price index for natural gas, southwest Kansas.

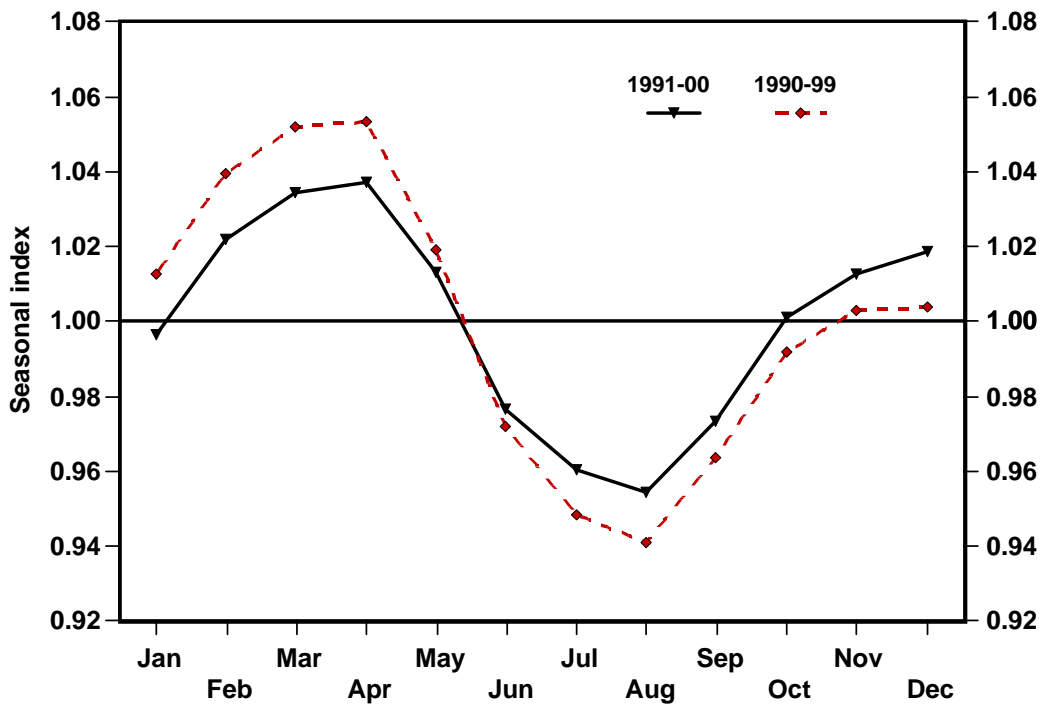


Figure 8. Seasonal price index for anhydrous ammonia (NH3), midwest U.S.