HOW MUCH WOULD IT BE WORTH TO KNOW THE WASDE REPORT IN ADVANCE?

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WASDE REPORT IN ADVANCE?

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Abstract: Past research has shown that prices move in response to WASDE reports, but have only looked at price movements immediately prior to and after a report. This research seeks to determine the profitability of trading based on knowing the next WASDE report at the time of the current report. This should help traders evaluate investments in efforts to predict the information contained within the report. The commodities used in the model are US corn, soybeans, and wheat. The variable position and rolling regression models are price forecasting models that use an ending stocks regression to forecast price at the next WASDE report release. For the variable position model, the intercept is calibrated so that the model predicts the current price without error; the slope is based on report data from no more than the last two years of data. The rolling regression model uses a specified amount of historical data from one to five years in its regression. Using the forecasted price, the position of the trading model's profit calculation can change daily based on where the closing price of the commodity is in relation to the price prediction. These two models are compared to determine the optimal amount of historical information to include in the price forecast. The trade and hold model is used to determine the profits of trading based on whether ending stocks will be up or down at the next WASDE report. Profits are averaged on a days until report, monthly, and yearly basis. The variable position model and rolling regression model show a steady return to trading over the report month. The trade and hold model shows an increase in profits on the report release day. Ending stocks and predicted yield account for a small yet very important part of market movements. Trading models that include more information are needed to produce accurate price forecasts. Trading close to the report, during the growing season, and trading historically important WASDE reports that contain finalized information are the keys to maximizing trading profitability.

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CHAPTER I

INTRODUCTION

The United States Department of Agriculture (USDA) releases monthly World Agricultural Supply and Demand Estimates (WASDE) which contain fundamental market information such as the National Agricultural Statistics Service (NASS) crop production reports, and ending stocks estimates. The USDA releases crop production reports that provide estimates of corn, soybean, and wheat yield which are included in the WASDE reports. Private firms attempt to predict the WASDE reports using satellite imagery, publicly known supply and demand estimates, experimental plots, crop tours, and calls to grain firms as well as many other ways to gather fundamental information (Milonas 1987).

The objective of this research is to determine the value of WASDE report predictions in the days before the report is released and the optimal use of the predicted information. Many agricultural economists have studied the effects of USDA crop production reports on commodity prices. Findings by Adjemian (2011), Fortenbery and Sumner (1993), Isengildina, Irwin, and Good (2006); Isengildina-Massa et al. (2008); McKenzie (2008); Milonas (1987); and Sumner and Mueller (1989) confirm that WASDE reports contain significant fundamental market information that causes market prices to change after the reports are released. Adjemian and

Smith (2012) declare that USDA crop production reports cause "unmistakably significant" changes in market prices. A trading firm that could predict these market movements would have incentive to gather relevant and accurate information to develop their forecast models. This research is important to private firms because it will provide a daily value of the predictions leading up to the report. This research can be used by traders to determine how many days, before the report is released, it is profitable to use their predicted WASDE information.

These reports are released on a monthly basis and contain information compiled by several USDA agencies such as NASS; the reports offer information on supply and demand and contain two main components, acres to be harvested and expected yield per acre (Vogel and Bange 1999). The NASS Crop Production report and the WASDE report are developed secretly and are released between the 9^{th} and 12^{th} of every month (Vogel and Bange). One particular piece of information in the reports are the projections. WASDE projections are released for a projection year normally beginning in May and ending in April of the next calendar year. According to the September 17, 1973 WASDE report, these projections are meant to serve as a guideline approximation based on the information currently known. These projections are representative of a wide range rather than a precise estimate; they vary with every new WASDE as crop, weather, and economic conditions change. These reports have a dramatic effect on markets because the information remains secret until the official report release. The USDA fiercely guards this information to insure that nothing is leaked before the report date (Vogel and Bange). This ensures that no participants gain access to the information before others.

The USDA reports have been very influential in causing extreme price movements in otherwise stable markets (Isengildina, Irwin, and Good 2006). Sumner and Mueller (1989) found that the harvest forecast reports released in the months of August, September, and October cause a greater change in corn and soybean market prices than other reports. Known periods of greater market realignments offer traders a chance to capitalize on market movements. Adjemian (2011) found that "virtually all" of the WASDE reports that contained NASS crop production reports stood out as significant. The struggle of private firms is to determine what direction the market will move based on the new information contained in these reports. Private agencies already release prediction data in the days prior to a USDA report (McKenzie 2008). One could argue that if this data were totally accurate and in turn negated the need for WASDE reports, it would remove the volatility from the market in the days before a report. This is clearly not the case. Isengildina-Massa et al. (2008) found that after WASDE reports containing NASS crop production reports were released, implied volatility in corn and soybean markets was reduced by an average of 2 and 2.5 percentage points 89% and 100% of the time, respectively. This makes a strong case that private firms are not able to predict all of the information that is contained in the NASS crop production reports.

The establishment of the relevance of WASDE reports has brought on a desire to predict the information contained in these reports. There are companies that have been effectively predicting at least parts of the crop production report (McKenzie 2008). However, the reports are still being released and continue to strongly affect the market. According to Fortenbery and Sumner (1993), this is because the NASS crop production reports change the supply and demand expectations and therefore alter the fundamental information collectively known by the market participants.

A few notable price forecasting models have been developed to predict grain prices. Anderson and Tweeten (1975), Westcott and Hull (1985), Westcott and Hoffmann (1999), and Do (2010) all used a form of stocks-to-use ratio or utilization to ending stocks ratio. Anderson and Tweeten (1975) set the precedent for wheat price prediction using these methods. Later work by Do (2010) updated the model to include new information from 1975 to 2008. The new model estimated by Do yielded a lower R-squared value for the regression than was obtained by Anderson and Tweeten (1975). A conclusion can be drawn here that it is detrimental to use very old data to predict new prices. There may also be evidence that the market experienced a structural change since the first model was developed. Suggested causes for recent structural changes are commodity index funds, ethanol mandates, and decreased supply. Mallory, Irwin, and Hays (2012) report that a third of the U.S. corn crop is being used in ethanol production. Westcott and Hull (1985) and Westcott and Hoffmann (1999) both analyzed the effect of different periods of government legislation on market behavior. The important finding by these researchers for the purpose of this model estimation is that futures price prediction models can be affected greatly by policy and structural change in the market. Therefore to accurately predict prices these models should only use data relevant to the current market structure and policy instead of using all of the historical information that is available.

Previous literature has shown the effects of WASDE reports a few days before the report release. However, past literature has not considered models of how to use predictions to trade. This research will study US corn, soybean, and wheat commodities spanning the years of 1975-2012. The main objective of this research is to determine the profitability of trading on a daily basis to determine what days are most profitable, and how long before a report release it is profitable to trade. Other information that will be provided includes details on seasonality through monthly profit calculations and whether there is evidence for structural change through yearly profit calculations. This research successfully fills a void in the current literature and serves as a relevant guide to the profitability of trading based on WASDE report information.

CHAPTER II

MODEL AND METHODS

To determine how much it is worth to know the WASDE report in advance, a profit equation utilizing a trading signal is developed. This trading signal is then calculated for four different models; the variable position, the rolling regression, and the trade and hold model. These models use ending stocks information for the independent variable of the regression. In addition to ending stocks, the rolling regression model is also run using predicted yield as the independent variable. The variable position model creates a trading signal that is triggered when the close price moves above or below the price forecast while using very recent historical data. The rolling regression model builds on the variable position model by specifying a fixed amount of data to be included in the regression in order to determine the optimal amount of historical data for a price prediction. Finally, the trade and hold model creates a trading signal based on the direction of ending stocks.

Profit Calculation

Profits for the trading models are calculated daily based on a trading signal. The system is always in the market with either a long or short position. The profit equation is:

(1) $$Profit_{d,m,t} = (-1)^{S_{d,m,t}} * (Close_{d,m,t} - Close_{d-1,m,t})$$

$$S_{d,m,t} \in \{0,1\}$$

$$0 = \text{long} \rightarrow -1^0 = 1$$

$$1 = \text{short} \rightarrow -1^1 = -1$$

where $Close_{d-1,m,t}$ represents the prior day's closing price, and $Close_{d,m,t}$ is the current day's closing price for day $d = 1, \dots D$, and report month $m = 1,2, \dots M_t$. The subscript $t = 1975, \dots T$ is representative of the WASDE projection year. $Profit_{d,m,t}$ indicates the profit for the current day. The variable $S_{d,m,t}$ is a binary trading signal where 0 signifies a long position and 1 a short position.

Variable Position and Rolling Regression Model

As suggested by previous literature, price forecasts are obtained using ending stocks regressions. Previous literature has shown the relationship between ending stocks and prices has changed over time, especially in recent years. To account for this structural change a regression model that heavily favors new market information is used. The linear regression is predicted for each WASDE report month using ending stocks (or predicted yield) information and the closing price on the day of the report. This general relationship is defined as:

(4) $$\boldsymbol{Price_c} = \beta_{1,c} + \boldsymbol{\beta_{2,c}}'\boldsymbol{x_c} + \boldsymbol{e_c}$$

here $\boldsymbol{Price_c}$ is a vector of the observed futures prices on the day of WASDE report releases for $c = m + \sum_{k=1975}^{t-1} M_k$. The parameters are updated with each new report. The vector for the variable position model is defined $\boldsymbol{Price_c} = \left(Price_{m(c),t(c)}, \dots, Price_{M_t(c),T(c)}\right)$. The coefficient $\beta_{1,c}$ is the intercept term. The vector $\boldsymbol{\beta_{2,c}}$ is the slope coefficients on the independent variables and $\boldsymbol{e_c}$ is a vector of error terms. The vector $\boldsymbol{x_c}$ is the independent variables. The subscript $m(c)$

is the WASDE report month in which the observation c is calculated. The subscript $t(c)$ is the projection year in which the observation c is calculated.

The independent variable for this model will be either inverse of projected ending stocks or predicted yield as reported in the WASDE report. The work of Anderson and Tweeten (1975), Westcott and Hull (1985), Westcott and Hoffman (1999), and Do (2010) provided the inspiration for the use of this model. Their models used a stocks-to-use ratio and utilization to ending stocks ratio. They use a ratio in an attempt to correct for structural change in the overall size of the market. A ratio is not used here since a relatively short time period is used.

Using the inverse of ending stocks helps capture the increased volatility of prices that is experienced when supplies get tight, while relaxing the effect of a change in ending stocks when supplies are large. For corn and soybeans vector $\boldsymbol{x_c}$ is equal to their own inverse of ending stocks. Wheat will include both wheat inverse ending stocks as well as corn inverse ending stocks. This is due to the fact that corn and wheat are substitutes for each other in animal feed. Wheat is considered a premium feed because it has a higher protein level. The price of wheat is usually above the price of corn since wheat costs more per bushel to produce. For this reason the corn price provides a floor price for the wheat market which wheat will rarely fall below. The rolling regression price vector is $\boldsymbol{Price_c} = (Price_{c-K+1}, \ldots, Price_c)$. Here $K = 12{,}24 \ldots 60$. The rolling regression is also used with predicted yield data as the independent variable. In the wheat model, both wheat predicted yield and corn predicted yield are included as independent variables.

For the generalized model specification the predicted price equation is as follows:

(5) $$\widehat{Price}_{c+1} = \bar{\beta}_{1,\mathrm{c}} + \boldsymbol{\bar{\beta}'_{2,c} x_c}$$

where $\widehat{Price}_{c+1}$ is a scalar forecasted price for the next WASDE report release. The intercept coefficient $\bar{\beta}_{1,c}$ and the vector $\bar{\boldsymbol{\beta}}_{\boldsymbol{2},\boldsymbol{c}}$ are a calibrated intercept and slope coefficient.

The slope coefficient for the variable position model is calculated using a weighted average of the previous year's last regression's slope and the slope from this year. The decision to limit the use of the previous year's regression slope coefficient in this manner is because the model is using only the current year of data. The model's accuracy was low early in the year when there is limited information. Slowly throughout the year the slope is weighted more to the current year than the previous year and in the last month does not use any of the previous slope estimation. The weighted average slope coefficient for the variable position model is under restriction:

(6) $$\bar{\beta}_{2,c} = \max\left(\frac{\min\,(m(c),10)}{10} * \hat{\beta}_{2,m(c),t(c)} + \left(1 - \frac{\min\,(m(c),10)}{10}\right) * \beta_{2,M(c),t(c)-1}, 0\right)$$

The coefficient $\hat{\beta}_{2,m(c),t(c)}$ is the current predicted slope coefficient and $\beta_{2,M(c),t(c)-1}$ is the last slope coefficient from the previous year. The calibrated slope coefficient is restricted to be greater than zero.

The slope coefficient for the rolling regression model is expressed here under restriction:

(7) $$\bar{\beta}_{2,c} = \max(\hat{\beta}_{2,c}, 0)$$

where $\hat{\beta}_{2,c}$ is the predicted slope coefficient and cannot be less than zero.

The intercept coefficient for the variable position and rolling regression models is calibrated:

(8) $$\bar{\beta}_{1,c} = Close_c - \bar{\boldsymbol{\beta}}_{\boldsymbol{2},\boldsymbol{c}}{}'\boldsymbol{x}_{\boldsymbol{c}}$$

allowing the intercept coefficient $\bar{\beta}_{1,c}$ to be calibrated so that the function passes through the closing price.

To calculate profit the variable position and rolling regression models use the trading signal:

(9) $$S_{d,m,t} = \begin{cases} 0 \text{ if } \widehat{Price}_{c+1} > Close_{d-1,m,t} \\ 1 \quad \text{otherwise} \end{cases}$$

here if the forecasted price $\widehat{Price}_{c+1}$ is greater than yesterday's close price $Close_{d-1,m,t}$ then a long position is opened. Otherwise the equation returns a 1 to open a short position. The forecasted price is for WASDE report month $m + 1$. Since the subscript c corresponds to the current month m.

Perfect Foresight

In order to determine the effectiveness of the models to generate profits, the models were run normally, and under a perfect foresight method. This "perfect foresight" was applied to the variable position model and the rolling regression model. The perfect foresight is run for every model because the variable position model does not provide a price forecast unless two observations are observed in the current WASDE projection year. Also, the rolling regression model does not provide a price forecast unless the required observations for the regression have been observed. By using the actual closing price in place of the forecasted price, a total profit of the model could be calculated. The trading signal for the perfect foresight model is:

$$S_{d,m,t} = \begin{cases} 0 \text{ if } Close_{1,m,t} > Close_{d-1,m,t} \\ 1 \quad \text{otherwise} \end{cases}$$

here trades are made based on if the closing price on the report release day is larger than the yesterday's closing price. A value of 0 indicates a long position and 1 indicates a short position.

These models provide the information necessary to determine the value of predicting WASDE reports. The trade and hold model is useful in identifying the potential profit from trading based only on the expected direction of the change in ending stocks as opposed to trying to accurately predict what they will be. The variable position model makes trades based on the price forecast. The rolling regression model builds on the variable position model by including varying levels of old data to determine the optimum amount of data to include in the prediction.

Trade and Hold Model

The trade and hold model is based only on the direction of change in WASDE ending stocks. If ending stocks went down in the future month, a buy indicator was triggered; if ending stocks went up a sell indicator was triggered:

$$S_{d,m,t} = \begin{cases} 1 & \text{if } ES_{m+1,t} > ES_{m,t} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $S_{d,m,t}$ is the current day's trading signal for the profit equation (1). The variable $ES_{m+1,t}$ is the ending stocks for the next month, $ES_{m,t}$ is the ending stocks for the current month.

Total Market Movement

To help explain the seasonality of corn, soybeans, and wheat the total market movement of each commodity was calculated using the trading signal:

$$S_{d,m,t} = \begin{cases} 1 & \text{if } Close_{d,m,t} - Close_{d-1,m,t} < 0 \\ 0 & \text{otherwise} \end{cases}$$

The total market movement can be used to determine which days and months have the largest market movement independent of a trading model. This is beneficial because it does not depend on an estimation of price and can provide insight as to when the opportunity for the most profit occurs, and what times have the most potential for large profits.

CHAPTER III

PROCEDURE AND DATA

This research uses a variable position model, rolling regression model, and a trade and hold model to provide trading signals for a profit calculation. These models require price information that quickly reflects changes in WASDE report information. Once profits are calculated it is important to sort the profits by the WASDE report month projection year so that inferences on the effects of the WASDE report can be made.

Model Estimation

Profits are calculated for the variable position model and the rolling regression model based on a trading signal. This trading signal is determined by a price forecast generated from the regression estimation of WASDE US ending stocks on futures prices. The following is a guide to help explain the forecasting and profit calculation process.

The Variable Position Model:

- Historical WASDE US ending stocks are regressed on historical futures prices.

- A price forecast is calculated for a WASDE report month by using the next WASDE report's actual observed ending stocks (this represents a perfect prediction of ending stocks).
- The trading signal for the variable position model creates a buy/sell indicator using the price forecast from the previous step. This buy/sell indicator is a 0 for a long position and a 1 for a short position.
- The profit calculation uses the buy/sell indicator to calculate profit by multiplying the trading signal by the difference of today's closing price and yesterday's closing price.

The calculation of profit is entirely in sample so that perfect predictions of ending stocks can be made. Application out of sample would require an estimation of ending stocks. An example of the SAS code used is included in the appendices of this paper in figure 17.

The Corn and Soybean Model

Corn and soybeans, unlike wheat, are homogeneous and traded on one exchange, the CME. Their closing prices are directly regressed on WASDE US ending stocks or predicted yield data.

The Wheat Model

Wheat is a commodity that is used for animal feed as well as human consumption. Wheat has a higher protein level than corn so therefore it is considered a premium feed when fed to animals. For this reason the wheat price will generally be higher than corn. In years when corn is in low supply, it can cause the wheat price to increase in value as cattle feeders substitute wheat for corn. For this reason, the variable position and rolling regression wheat models will include corn ending stocks as well as wheat ending stocks to account for corn's influence on the wheat price. In addition, wheat is marketed by class and individual wheat class information is reported in the WASDE report from 1980 to the present. The different wheat classes represent various varieties of wheat that are grown for specific purposes and during different growing periods throughout the year.

The WASDE US wheat ending stocks is the sum of hard red winter, soft red spring, hard red spring, durum, and hard white wheat. Using only one exchange to trade the commodity would put an uneven weight on that price and the growing conditions of the crop traded there. Soft red winter, hard red winter, and hard red spring wheat classes are primarily traded on the CME, KCBT, and MGEX respectively. White and durum wheat are produced in a smaller quantity than the other three classes so they are not included in the calculation. Therefore, the closing prices of the three exchanges were weighted based on the production bushels that were reported in the WASDE wheat by class reports:

$$\overline{Close}_{d,m,t} = \sum_{i=1}^{3} w_i p_i \tag{19}$$

$$w_i = \frac{q_i}{\sum_{i=1}^{3} q_i}$$

where variable $\overline{Close}_{d,m,t}$ is the weighted average close price. The subscript $i = 1,2,3$ represents the three classes of wheat; hard red winter, soft red winter, and hard red spring wheat. The weighting variable w_i is the weighted average of the WASDE production numbers for three classes of wheat. The variable p_i represents the daily closing price of the KCBT, CME and MGEX exchanges and q_i is the sum of the production projections for all WASDE wheat by class reports observed[1]. The weighted average close price is then used throughout the model estimation and profit calculations.

Data Transformation

The data displayed visual signs of heteroscedasticity due to increased prices and the subsequent

[1] The actual estimated weights are KCBT=0.44, CME=0.27, and MGEX=0.29.

increase in volatility of futures prices starting around the year 2008. An estimated generalized least squares (EGLS) approach was taken. To correct for this, the daily profit calculations were weighted by running a regression with the actual profits from the trading model:

(14) $$Profit_t = \beta_0 + \varepsilon_t$$

where $Profit_t$ is the regression of daily profits without explanatory variables. The intercept term β_0 serves as a mean of the profits. The log of the squared residuals $\hat{\varepsilon}_t$ is regressed on the class variable $Year$ to obtain the predicted variance which is represented by $\hat{\sigma}_t^2$. A weighting function is then calculated:

(17) $$Weight_t = \frac{1}{e^{\hat{\sigma}_t^2}}$$

where $Weight_t$ is the weighting variable for daily profit by year.

Sorting by Class Variables

The number of observations that trade off a particular WASDE report can vary depending on the day that WASDE report is released. Due to the varying calendar days each month and the untimely release of various WASDE reports, there is a wide range of report days that can be traded. An observation is identified by the number of calendar days from the next report it is. There are normally twenty-two trading days in a month but this day variable is based on calendar days, so thirty-one days were chosen to capture the total of any observed month.

Profits were reported based on the monthly WASDE reports. A simple use of the calendar month in which an observation was observed does not provide an accurate representation of which WASDE was used to trade. Knowing that the WASDE generally is reported early in the month, it is necessary to report the findings in terms of “report months” instead of “calendar months” so that one month does not report profits from two WASDE reports.

Yearly profits were sorted by the WASDE projection year. WASDE's projection years generally occur from May-April. If the profits were reported as calendar years then a similar problem to the monthly sorting would occur where the profits from two projection years would be reported for the same year. Additionally, contracts were not allowed to trade across contract years. Therefore, a WASDE report for the projection year had to be observed before a trading signal was produced. This results in lower observations in the months during the transition of projection years due to a lack of trading signal.

Once the profits of the commodities are calculated using the variable position model, the rolling regression model, and the trade and hold model daily profits are averaged together; this was done based on several class variables which were days, month, and year. These profits are all weighted as was described in equations (14-17). Daily, monthly and yearly averages will be helpful in determining the most profitable trading days, the effects of seasonality, and structural change.

Nonparametric Regression

A nonparametric regression allows representing the data with a function that is not bound by the common assumption of linearity. This type of regression performs well when there are a large number of observations. An analysis of the data without parameters allows structure in the data to be displayed visually that could be overlooked when using standard linear regression. One option for nonparametric regression is local regression. The locally weighted regression (LOESS) analysis calculates a local regression by fitting the regression to data with multivariate smoothing; the dependent variable is smoothed with a specified degree of freedom as a function of the independent variables in a moving pattern (Cleveland and Devlin). This research will use three degrees of freedom. This option gives a predicted value of the dependent variable at any given level of the independent variable. Therefore variables are smoothed for each observation of the independent variable. Benefits of the LOESS procedure are that it is suitable when there are outliers in the data and when robust fitting of the data is required. Restrictions of the LOESS procedure are that it requires a large number of observations to be precise and can be time consuming to calculate as local fitting occurs at every observation of the independent variable. An example from the GAM procedure with the LOESS model as provided by SAS is:

$$E(Y) = \beta_0 + \beta_1 x + s(x) \tag{11}$$

where $E(Y)$ is the predicted value of the dependent variable daily profit. The variable x is the independent variable days until report, β_0 is the intercept of the local regression, β_1 is the trend term, and $s(\,)$ is the nonparametric smoothing function of the independent variables. Then a plot of the predicted smoothing components on days until report is created.

Data

The WASDE reports are released on a monthly basis and contain information for many different agricultural commodities. They include information at the United States and world level to provide information on the current supply of commodities and expected acreage and yield data. The WASDE report releases a part of its information as projections. These projections are categorized in projection years that generally span May through April. As defined in the September 17, 1973 WASDE, the projections are meant to serve as a guide to the coming crop that is representative of a wide range of possible values that is based on presently available data. The projections can change as more information about economic conditions, availability of inputs, and crop and weather conditions are reported. Each new WASDE contains a new projection that will represent the most current information gathered during that report month. As mentioned earlier the projections generally begin between May and April; the exception is the early WASDE reports from September 17, 1973 through 1979. During this time period there was not a standard in which the projection year began which allowed it to vary among the early months in the calendar year. The March contract is used in order to capture a majority of the projection year. The only month of the calendar year that would not report profits is April due to the March contract expiration and a new WASDE report for the next contract year not becoming available until May. However, when the projection years began earlier than May, some observations in April were allowed to be traded.

The WASDE periodically releases reports that contain corrections for previous WASDE information. These corrections are generally a small difference in the previously reported numbers and do not provide a large amount of new information to the market. As such these reports were not included in this data set. Of the 533 WASDE reports released from September 17, 1973 to March 8, 2013 that contained US corn projections, 38 of these reports contained corrections to corn ending stocks and the ending stocks changed on average by 4.24% of the original number. The largest changes from the corrections occurred in WASDE reports that were released in the 1970s.

Futures Prices

The variable position and trade and hold models use corn and soybean ending stocks information which is reported in millions of bushel. The rolling regression model will be estimated twice using ending stocks information and then predicted yield data. Futures prices are from R&C research at www.price-data.com. Corn and soybean data are from the Chicago Mercantile Exchange Group (CME) and are reported in dollars per bushel.

Generally, soft red winter wheat is traded on the Chicago Board of Trade (CBOT), hard red winter wheat is traded on the Kansas City Board of Trade (KCBT), and hard red spring wheat is traded on the Minneapolis Grain Exchange (MGEX). These three wheat classes represent the majority of the wheat traded on the three exchanges.

CHAPTER IV

RESULTS

The results of this research are reported as average daily profits by days until report, WASDE report month, and WASDE projection year. The results provide information pertaining to the most profitable trading days and which WASDE reports are the most profitable to trade. This allows inferences to be made on the effectiveness of the information in the reports to move markets and arguments for seasonality and structural change to be discussed.

Variable Position Model

The variable position model provides a price forecast for trading in a unique way by calibrating the slope coefficient of the regression using a weighted average of the previous projection year's last slope coefficient, and the current projection year's new information. This allows the regression to adapt to new market information quickly. Also, the intercept coefficient is calibrated to pass through the closing price on the day of the last WASDE report release. This insures that the regression will provide a price forecast that is similar to the previous month and reduces large movements in predicted prices.

The last intercept and slope of the WASDE projection year are retained from the model estimation so they can be plotted to show the change in the beta coefficients across WASDE projection years. These are displayed in figures 1, 3, and 5 for corn, soybeans, and wheat.

The intercept coefficients stay relatively constant throughout the sample period for all commodities. There are a few exceptions most notably around the years 2007 and 2008. By calibrating the intercept so that the regression line travels through the last known price, the variance of the intercept coefficients is reduced. This ensures that there are no wild breaks in predictions across months and that the regression of the price forecasts will include the last known price.

The coefficients for slope tend to vary more over time. As the market structure has changed in recent years the variance of the slope coefficients has become large compared to earlier observations. To combat this, the variable position model uses a moving average approach that combines estimates with the data from the year immediately prior and the current estimates. This helps alleviate the effect of structural change by using very new data in the regression. All three commodities experience a major change in slope coefficients around the year 2008. As was discussed earlier in this paper, some have attributed this to index funds, ethanol mandates, and overall lower supplies which tighten supplies and lead to a greater slope of the regression line. At these low quantities, prices tend to make larger moves with changes in supply (inelastic demand).

In Figure 2 the final slope coefficients for corn display a trend of increasing volatility over the data set. At the year 2008 there is a change in the trend which results in large coefficients from 2009 to 2012. The market appears to respond more dramatically to changes in ending stocks than it has in the past which is in part due to the inelastic demand for corn when ending stocks are low.

In Figure 4 the final slope coefficient for soybeans is much more volatile than what is observed in corn. There are large increases in the slope coefficients at various times in the data set but like with corn, there is an change in 2008. Slope coefficients become large compared to recent years and continue to vary each year up to 2012.

The wheat final slope coefficients are reported in Figure 6 and they show similar results to soybeans. There is a large increase in the slope coefficients around 2008 and they change dramatically for the subsequent years up to 2012.

These figures show that the market experienced a sudden change around the year 2008. The model is able to adjust to this structural change quickly due to the use of new data in the calculation of the slope coefficient and adapted to the current market structure.

The estimates of the nonparametric regressions are shown in figures 14-16. This is not a plot of cumulative profits, but rather, a plot of the predicted profit on a per day basis. These are smoothed profits and reveal that on average the model is profitable with an upward trend moving toward the report release date for corn and soybeans. Unexpectedly, the figure for wheat showed a reduction in profits as the report release approached. The corn and soybean figures 14 and 15 show movement that would be expected when the market is obtaining information as the report release date approaches. Possibly it is because private firms are beginning to predict at least parts of the report. The wheat trend in Figure 16 suggests that US ending stocks is not a good predictor of wheat prices and that the information released in the WASDE report is not the major cause of price movement.

The variable position model for US corn does not generate a larger profit on average for the report release day. The results in Table 1 show a significant amount of noise in the market as is inferred from the wide range of profits. There is a slight increase in profits on the report release day but it is difficult to determine if there is a pattern. In order to determine if there is a trend in profits nonparametric regression is used to robustly fit the data. Figure 14 shows that the profits tend to increase as the report release approaches. This increase becomes more pronounced at fifteen days before the report and continues to increase until the report release day. From Table 4 the average daily profit over the entire data set for corn was 0.22 cents per bushel. As reported in Table 5, the perfect foresight trading signal made an average daily profit of 1.09 cents per bushel. Therefore the corn model estimation was successful at capturing 20.18% of available profits. There appears to be value in predicting the reports at least fifteen days before the report as is shown with nonparametric regression, however, the amount of noise in the market provides evidence that there are other factors affecting the market as well.

Monthly data offers the opportunity to determine the effect of the growing cycle, and the collection of harvest data, on price. Also it offers a way to determine which reports provide the most influential information to the market. Some reports include NASS crop production data and provide crop condition and yield data to the market. The monthly profits calculations from Table 6 show that July, September, and February are the most profitable to trade corn. The perfect foresight trading signal returned the largest profits in July, August, and October as shown in Table 7. The corn crop is very susceptible to changes in weather during the peak of its growing season. This helps explain why July and September are profitable to trade; changes in weather and crop conditions cause prices to move and become more volatile during July and August. February is likely a profitable month due to the finalized harvest and ending stocks information released in this report. Typically January would be expected to be the most profitable year-end report but that is not what was observed here. The perfect foresight model shows that for corn, the largest opportunity for profits from the model occur towards the end of the growing season.

Soybeans returned results that were similar to corn. Average daily profit by days until report from table 2 show an increase in profits on the report day although the profits tend to be noisy. Nonparametric regression in Figure 15 shows a similar upward trend in profits as the report release day approaches. This uptrend occurred as far as twenty days before the report release. The average daily profit over the entire data set was 0.26 cents per bushel as shown in Table 4. The perfect foresight model returned an average daily profit of 2.91 cents per bushel shown in Table 5. Therefore, the model estimation for soybeans captured 8.94% of the total available profit. The model captured less available profits than the corn model did and this could be due to higher volatility in the soybean market coupled with less accurate price predictions. Interestingly, there appears to be a larger response to report information earlier in the report month than was observed in corn. This could mean that soybean markets are obtaining information more quickly than corn.

Soybeans most profitable months from Table 8 are January, September, and December. For soybeans the perfect foresight shown in Table 9 returned the largest profits in March, July, and August. Soybeans returned monthly results that show the year-end crop reports are more influential. Harvest information is contained in all three report months with increased emphasis on the January report. Historically traders regard this report as containing highly accurate harvest information for the US crop. Work by Isengildina-Massa et al. (2008) and Adjemian (2011) has already revealed the importance of the January crop reports due to the information on harvest data contained in them. Unlike corn, the soybean market is not influenced as heavily by weather and crop conditions during the growing season. A reason for this may be that soybeans are a large global market and are not as influenced by US information as much as corn. Interestingly, the perfect foresight model shows that early reports and the August report offer the largest opportunity for profits. This is in contrast to corn where the largest profits can be obtained in the latter part of the growing season. It appears that the US soybean crop has a small impact on soybean markets and other information is affecting the market.

The average daily profits for wheat are low compared to corn and soybeans. In Table 3 profits are small and negative with a negative profit returned on the report release day. Again the profits are very noisy so nonparametric regression was used to look for trends in the data. Figure 16 shows that the profitability of wheat decreases as the report release day approaches. The largest profits are observed before twenty days until the report release. It does not appear that US wheat provides enough information in order to predict wheat futures prices.[2] Wheat returns an average daily profit of -0.04 cents per bushel as reported in Table 4. From Table 5 the perfect foresight model produced an average daily profit of 1.24 cents per bushel. The price forecasts from the regression are not accurate enough to produce a positive average daily profit for the wheat model. There are other factors driving the market in addition to ending stocks that must be included to provide an accurate price forecast.

The most profitable months to trade wheat as shown in Table 10 are August, September, and December. The perfect foresight model shows that the largest market movements occur in July, October, and February as reported in Table 11. While these are the most profitable months to trade, it should be noted that the profits are very small and a majority of the other months return negative profits. When trading wheat it is important which months are chosen to trade. The timing of WASDE projection years and the presence of different classes of wheat makes it difficult to analyze seasonality. The winter wheat classes are being harvested at the beginning of a new WASDE projection year so part of the growing season is not included in the profit calculations. Also, using a weighted average of the three exchanges negates observing the influence of ending stocks on any one class of wheat.

Yearly profits are calculated to study structural change and are displayed in Figure 9, 11, and 13. Sudden changes in market structure due to policy changes, the economic climate, or

[2] The model is run using world wheat and world corn ending stocks, and by US wheat by class ending stocks to determine the fragility of the above model. The world wheat and corn model uses the weighted average closing price. The US wheat by class models use futures prices from the CME for soft red winter, the KCBT for hard red winter, and the MGEX for hard red spring wheat. Average daily profits when using world wheat and corn are 0.11 cents/bushel. The profits for wheat by class are soft red winter 0.3 cents/bushel, hard red winter -0.6 cents/bushel, and hard red spring -0.07 cents/bushel. While the world wheat and corn information returns larger profits than US wheat and corn, the profits are not statistically significant and are still small. However, there is marked improvement in the profitability using world information.

weather patterns can dramatically affect the profitability of a trading model. An increase in slope coefficients from the variable position model coincides with an increase in the volatility of average daily profits. While the model tends to adjust favorably to the structural change with resulting large profits, recent profits have waned. Corn has remained the most profitable as shown in figure 9. Profits increase in 2009 and peak in 2011. Soybean profits in Figure 11 show a favorable increase in profits with a corresponding negative downturn in 2012. The wheat results in Figure 13 are similar to soybeans with large profits in 2008 then turning negative in 2012.

Rolling Regression Model

The rolling regression model allows the use of more data to determine the optimal amount of historical information to include in the regression estimation. Two models, one for ending stocks and one for predicted yield, are used.

The average daily profits by days until report are found in Tables 12-14 and show similar results to the variable position model where the profits are very noisy with no obvious trends in profitability. It is important to note that with the exception of wheat, corn and soybean profits do not increase when more historical information is included in the model as seen in Table 4. Furthermore, wheat only increased slightly in profitability. The variable position model produces the most accurate price forecasts and resulting higher profitability due to only using new data and adapting to current market conditions quickly.

In addition to using ending stocks to predict the price on the report release day, predicted yield was used. The largest average daily profits are observed with 24, 60, and 12 observations for corn, soybeans, and wheat respectively. This produced the largest average daily profits equal to 0.11, -0.06, and 0.4 cents per bushel for the three commodities as shown in Table 4. Table 5 reports that the perfect foresight made a profit of 0.97, 2.41, and 1.17 cents per bushel for the three commodities. This results in the corn model capturing 11.34% of the market movement as well as wheat capturing 3.42%. This is evidence that US predicted yield information is a good predictor of corn prices. Wheat and soybeans did not fare well when yield was used to predict the price forecast. It may be that wheat and soybeans are too largely affected by world markets so predicted US yield does not have enough predictive power.

Monthly profits are shown in tables 15-20. These results are similar to the results found when using ending stocks in the variable position model and the rolling regression model. This is not unexpected as predicted yield is information reported by NASS. These results solidify the assumption that US crop information is affecting at least parts of the market and providing useful information to market participants. While the predictive power of predicted yield information is small, it was able to capture half of the profits that were obtained when using the variable position model with ending stocks information.

Trade and Hold Model

The trade and hold model provides a trading signal that is based on the direction of change in ending stocks across WASDE report months. This model is not dependent upon an accurate price forecast and is not allowed to change its trading signal throughout the month.

The daily profit calculations are found in tables 1-3. The trade and hold model shows that although the report release day is a very profitable day to trade, profits throughout the month are noisy as is observed with the variable position model. Average daily profits in Table 4 were calculated to be 0.33, 0.50, and 0.19 cents per bushel for corn, soybeans, and wheat respectively. These profits are larger than what was obtained by the variable position model because the trade and hold model does not require an accurate price forecast to determine the trading signal. The average daily total market movement in table 5 was calculated to be 3.01, 7.52, and 4.21 for the three respective commodities. The total market movement signal is useful in determining the average daily movement of the market; this provides insight into how much the market actually moves and the opportunity for profits. Monthly profits in tables 6-11 show similar results to the variable position model in which profits increase during critical growing periods and when important harvest information is released. Also, further evidence for structural change is found as all commodities became more profitable to trade from 2008 to the present.

The variable position model, the rolling regression model, and the trade and hold model all attempt to determine the profitability of trading on a daily basis as well as monthly and yearly average daily profits. The variable position model does not show evidence of large profits on the report release day from the raw data. Using nonparametric regression shows an upward trend in the relationship between profits and the days until report. Conversely, the trade and hold model finds an obvious increase in profits on the report release day. The three models also produced the largest profits during the commodities growing period, and when important WASDE reports were released that contained finalized harvest data. All three models show evidence of structural change that occurred around the year 2008. The variable position model and the trade and hold model show the largest return in profits and provide evidence that the best predictions result from using less historical data. The rolling regression model returns lower profits than the other two models and when yield data was introduced only corn was able to return positive daily profits. This leads to an assumption that the soybean and wheat markets are very much global markets that are not greatly influenced by US yield prediction data.

CHAPTER V

SUMMARY AND CONCLUSIONS

This research determines the value of a World Agricultural Supply and Demand Estimates (WASDE) report prediction on a daily basis for United States corn, soybeans, and wheat. The WASDE reports include projections that span from May to April of the next calendar year. These projections offer a general estimate of supply and crop information and represent a wide range of possible values rather than a precise number.

To calculate profits three models are used. The variable position model uses a forecast of the price on the day of a report release. To minimize the effect of structural change on the model a weighted average approach to calculate the slope coefficient on the model regression estimation is used. New regressions are developed for every month and the intercept coefficient is calibrated so that the most recent month's price is estimated without error. Then a trading signal determines the buy sell position depending on whether the previous day's closing price was above or below the price forecast. The rolling regression model determines the optimal amount of historical data to include in the regression for the price forecast. The number of observations included in the regression is varied from 12, 24, 36, 48, and 60 observations. Similar to the variable position model, the rolling regression model produces a price forecast that is used to determine the buy/sell position. The trade and hold model returns a buy/sell indicator based on whether ending stocks went down or up.

For the wheat model a weighted closing price is used. This weighted closing price consists of weighting the futures prices from the CME soft red wheat contract, the KCBT hard red winter wheat contract, and the MGEX hard red spring wheat contract by their respective production yield estimates as reported in the WASDE wheat by class reports. This closing price represents the change in prices that the three classes of wheat experience from the release of a WASDE US wheat projection. Using one exchange price would only represent the WASDE's effect on the major class of wheat traded on that exchange.

The profits from the model calculations are weighted using estimated generalized least squares. This accounts for periods of increased volatility to make the profits comparable across the entire data set. Without this weighting recent market activity would likely overshadow previous market conditions.

The results of these models indicate that it is more profitable to trade the WASDE report release days than other days throughout the month. This is because of the dramatic effect the information in these reports has on market prices. There is a relatively steady return to trading over the course of a report month along with a lot of noise in the profits. This suggests that it is unfavorable to trade a long way from the report as the majority of the profits can be realized on the report release day without subjecting a trader to undue risk in the market. Some of these risks are due to other information outlets such as various government reports that are released during the month that can affect markets independent of the WASDE reports.

Two methods of price forecasting are tested in this research. The variable position model includes a regression on ending stocks that limits new information by using a moving average slope coefficient. Old information is limited to the last slope coefficient of the previous year while new information is gradually introduced into the model. This model is very good at incorporating new information into the regression in order to account for structural change quickly. The rolling regression model uses ending stocks information and predicted yield. The purpose of this model is to determine if older information could increase the forecasting power of the regression. Observations included in the model are 12, 24, 36, 48, and 60. This is equivalent to using one year to five years of information. Each new report is added and the oldest report was dropped which rolls the regression over every month. Ending stocks information proves much more efficient at predicting futures prices than the predicted yield information. Corn is profitable with both methods but soybeans and wheat return very low profits with predicted yield information. Some reasons for this include that the information is of United States yield and soybeans and wheat are influenced by the world market. United States yield information does not influence prices enough to make an accurate prediction of price with that information alone. On average the variable position model is more profitable than the rolling regression model with the exception of wheat. This makes a case for using only very recent information in a price forecast. Using old information restricts the model and does not allow it to react to changes in market structure and price volatility. Wheat returns the largest profits with five years of ending stocks data, while this may just be noise in the profit calculation, it could be evidence that wheat has not responded to market influences in the same way corn and soybeans do.

The three commodities return different results for profitability by WASDE report month. This is due to crop growing periods and the weather and economic conditions that they encounter during this time. All commodities experienced increased profitability in the summer months. This is due to the fragile nature of the crop during the hot summer months and the weather conditions during this time greatly affect the potential yield of the harvested crop. Also, it is observed that traditional important crop reports at the end of a WASDE projection year are profitable to trade. This is attributed to the finalized ending stocks information that comes from these reports that are considered very accurate by traders. One observation that can be made is that it is most profitable to trade when the crop is at the peak of its growing cycle, and when final harvest numbers are gathered and deemed accurate. The rest of the WASDE projection year does not contain very profitable information to a trader trying to predict WASDE report information.

Evidence of structural change is observed for all three commodities when the average daily profits were sorted by the WASDE projection year they were observed in. Increased profits and price volatility occurs around the years 2007 and 2008. Some have attributed this to index funds, ethanol mandates, and overall tighter supplies which increase the price volatility of commodities. This is evidence that price forecasting models will need to be capable of limiting old information in order to account for this change. The market is behaving differently now so old trends will not be very successful at predicting future events.

This research determines that it is profitable to trade the WASDE report based on knowing the report information early. It does appear that a majority of the profits are realized on the report day and that there is a steady return to trading during the report month. While it can be profitable to trade even thirty-one calendar days away from the report release, the profits are very noisy and traders would be subjecting themselves to extreme risk due to the influence of other information sources causing market movement throughout the month. Knowing only ending stocks or predicted yield does not provide enough predictive power for a forecasted price to capture a majority of the market movement. More complex price forecasting models are needed to account for market movement as ending stocks and predicted yield account for a small yet very important portion of this movement. Trading close to the report, during the growing season, and trading historically important WASDE reports that contain finalized information are the keys to maximizing trading profitability.

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TABLES AND FIGURES

Table 1. US Corn Average Daily Profit Cents/Bushel by Days Until Report

Days Until	Trade and Hold		Variable Position	
Report	Profit	t-Value	Profit	t-Value
0	1.03	3.44	0.49	1.34
1	0.10	0.44	0.05	0.21
2	0.00	0.00	0.22	0.90
3	0.01	0.04	-0.15	-0.46
4	0.26	0.84	0.26	0.75
5	0.20	0.71	0.36	1.25
6	0.27	1.14	0.04	0.15
7	0.32	1.38	0.55	2.28
8	0.34	1.42	-0.10	-0.38
9	0.54	1.67	0.48	1.43
10	0.25	0.79	0.43	1.24
11	0.85	2.55	0.13	0.35
12	0.96	2.61	0.32	0.77
13	0.23	1.07	0.27	1.18
14	0.05	0.20	0.21	0.87
15	0.64	2.65	0.20	0.76
16	-0.70	-2.52	0.26	0.87
17	-0.20	-0.68	0.31	0.98
18	0.26	0.95	-0.13	-0.45
19	0.12	0.45	0.13	0.42
20	0.61	2.39	0.45	1.59
21	0.78	3.60	0.33	1.34
22	0.60	2.39	0.34	1.21
23	-0.13	-0.48	-0.01	-0.05
24	0.27	0.86	0.37	1.04
25	0.25	0.84	-0.06	-0.16
26	0.10	0.33	-0.06	-0.19
27	0.23	1.07	-0.01	-0.03
28	0.29	1.21	0.05	0.18
29	0.76	2.28	0.65	1.63
30	0.95	1.44	0.88	1.19
31	-0.55	-0.93	-0.25	-0.34

Table 2. US Soybeans Average Daily Profit Cents/Bushel by Days Until Report

Days Until	Trade and Hold		Variable Position	
Report	Profit	t-Value	Profit	t-Value
0	2.44	3.60	1.05	1.18
1	0.73	1.29	0.13	0.20
2	0.71	1.16	0.80	1.17
3	0.17	0.23	-1.22	-1.50
4	0.95	1.18	0.24	0.24
5	0.72	0.98	2.18	2.68
6	0.13	0.23	0.11	0.18
7	0.39	0.70	0.18	0.28
8	0.53	0.91	-0.29	-0.43
9	0.32	0.40	-0.28	-0.33
10	0.84	1.20	0.68	0.84
11	2.38	3.21	0.29	0.32
12	0.84	0.98	-0.65	-0.65
13	0.75	1.24	1.99	2.92
14	-0.19	-0.38	0.00	0.01
15	0.81	1.42	0.65	0.99
16	-0.19	-0.27	0.12	0.16
17	-0.06	-0.08	-0.22	-0.28
18	0.87	1.23	-0.60	-0.71
19	0.45	0.66	-0.21	-0.27
20	-0.73	-1.27	0.02	0.03
21	0.89	1.77	1.14	1.90
22	0.36	0.60	0.24	0.33
23	-0.64	-1.04	-0.63	-0.87
24	0.05	0.07	-0.35	-0.39
25	0.37	0.52	-0.22	-0.24
26	-0.28	-0.38	0.24	0.27
27	0.65	1.24	1.08	1.80
28	0.72	1.23	0.26	0.36
29	-0.17	-0.25	1.00	1.19
30	0.78	0.54	-0.85	-0.43
31	-1.72	-1.69	-2.30	-1.35

Table 3. US Wheat Average Daily Profit Cents/Bushel by Days Until Report

Days Until	Trade and Hold		Variable Position	
Report	Profit	t-Value	Profit	t-Value
0	1.26	3.17	-0.41	-1.04
1	0.11	0.36	-0.05	-0.16
2	0.04	0.11	-0.68	-1.93
3	-0.56	-1.47	-0.85	-2.44
4	-0.62	-1.25	0.36	0.70
5	0.67	1.57	-0.12	-0.29
6	-0.10	-0.30	0.21	0.63
7	0.09	0.27	0.17	0.52
8	0.65	1.92	-0.56	-1.54
9	0.59	1.46	0.10	0.26
10	0.16	0.40	-0.05	-0.12
11	0.75	1.57	-0.84	-1.73
12	-0.13	-0.22	1.18	1.85
13	0.07	0.22	0.52	1.85
14	-0.31	-1.05	0.16	0.57
15	0.61	1.23	-0.09	-0.18
16	-0.36	-0.93	-0.58	-1.52
17	-0.41	-0.99	0.61	1.45
18	0.71	1.88	-0.32	-0.89
19	-0.18	-0.52	-0.72	-2.08
20	1.00	3.44	0.24	0.70
21	0.15	0.59	-0.06	-0.21
22	0.84	2.46	0.39	1.11
23	0.43	1.20	0.53	1.28
24	0.06	0.15	0.07	0.19
25	-0.06	-0.16	0.24	0.67
26	0.19	0.45	0.20	0.49
27	0.05	0.19	-0.45	-1.59
28	-0.14	-0.41	-0.76	-2.17
29	-0.58	-1.59	0.35	0.74
30	1.23	1.34	1.02	0.95
31	-0.70	-0.88	-0.52	-0.57

Table 4. US Corn, Soybeans, and Wheat Average Daily Profit Cents/Bushel

	Corn		Soybeans		Wheat	
Model	Profit	t-Value	Profit	t-Value	Profit	t-Value
Trade and Hold	0.33	6.70	0.50	4.29	0.19	2.85
Variable Position	0.22	4.09	0.26	1.90	-0.04	-0.58
Rolling Regression						
<u>Ending Stocks</u>						
12 Months	0.17	3.55	0.24	1.86	0.02	0.40
24 Months	0.18	3.59	0.23	1.76	0.05	0.89
36 Months	0.16	3.30	0.24	1.89	0.02	0.34
48 Months	0.14	2.65	0.19	1.44	0.02	0.42
60 Months	0.12	2.40	0.18	1.36	0.06	1.05
<u>Yield</u>						
12 Months	0.08	1.56	-0.17	-1.30	0.04	0.63
24 Months	0.11	2.14	-0.12	-0.94	0.00	-0.01
36 Months	0.07	1.43	-0.08	-0.60	-0.09	-1.42
48 Months	0.03	0.65	-0.12	-0.92	-0.05	-0.96
60 Months	0.01	0.21	-0.06	-0.45	-0.04	-0.73

Table 5. US Corn, Soybeans, and Wheat Average Daily Profit Cents/Bushel
Total Market Movement and Perfect Foresight Trading Signal

	Corn		Soybeans		Wheat	
Model	Profit	t-Value	Profit	t-Value	Profit	t-Value
Trade and Hold	3.01	75.31	7.52	86.49	4.21	63.22
Variable Position	1.09	20.56	2.91	21.76	1.24	17.98
Rolling Regression						
<u>Ending Stocks</u>						
12 Months						
24 Months	1.01	21.45				
36 Months			2.72	21.73		
48 Months						
60 Months					1.20	20.55
<u>Yield</u>						
12 Months					1.17	19.29
24 Months	0.97	20.05				
36 Months						
48 Months						
60 Months			2.41	19.43		

Table 6. US Corn Average Daily Profit Cents/Bushel by WASDE Report Month

WASDE	Trade and Hold Model			Variable Position Model		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	772	-0.03	-0.24	751	-0.06	-0.54
2	692	0.19	1.28	659	0.27	1.74
3	669	0.46	3.11	625	0.00	0.00
4	273	0.21	0.89	23	0.16	0.12
5	65	-0.84	-1.93	23	-0.96	-0.97
6	699	0.12	0.81	62	-0.39	-1.06
7	703	0.61	2.77	671	0.65	2.84
8	839	0.76	4.12	838	0.22	1.19
9	802	0.40	2.50	802	0.33	2.01
10	805	0.42	2.48	805	0.30	1.76
11	797	0.51	3.58	797	0.21	1.46
12	784	0.04	0.30	784	0.24	1.72

Table 7. US Corn Average Daily Profit Cents/Bushel by WASDE Report Month for Total Market Movement and Perfect Foresight

WASDE	Trade and Hold Model			Variable Position Model		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	772	2.14	22.73	751	0.47	4.19
2	692	2.44	18.70	659	1.08	7.02
3	669	2.62	21.37	625	0.92	6.32
4	273	2.68	15.51	23	0.99	0.75
5	65	2.68	9.17	23	-0.30	-0.30
6	699	2.92	25.39	62	0.63	1.73
7	703	4.24	25.09	671	1.39	6.25
8	839	3.97	29.37	838	1.61	8.96
9	802	3.28	27.48	802	1.19	7.61
10	805	3.18	21.59	805	1.22	7.30
11	797	2.74	22.75	797	1.02	7.28
12	784	2.62	22.51	784	0.96	7.00

Table 8. US Soybean Average Daily Profit Cents/Bushel by WASDE Report Month

WASDE	Trade and Hold Model			Variable Position Model		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	709	0.05	0.14	709	0.63	1.70
2	667	0.63	1.63	666	0.29	0.83
3	776	0.68	1.74	640	-0.25	-0.59
4	311	0.63	1.33	.	.	.
5	713	-0.18	-0.55	12	-1.00	-0.21
6	731	0.15	0.42	46	0.32	0.25
7	761	1.90	3.84	724	0.33	0.64
8	817	0.39	0.85	817	-0.56	-1.19
9	802	0.88	2.12	802	0.68	1.66
10	805	0.75	1.79	805	0.14	0.32
11	782	0.29	0.82	782	0.35	1.03
12	765	-0.16	-0.43	763	0.82	2.18

Table 9. US Soybean Average Daily Profit Cents/Bushel by WASDE Report Month for Total Market Movement and Perfect Foresight

WASDE	Trade and Hold Model			Variable Position Model		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	709	6.28	25.57	709	2.23	6.11
2	667	6.66	22.47	666	2.23	6.71
3	776	7.16	23.72	640	3.17	7.61
4	311	5.89	16.79	0	.	.
5	713	5.98	25.12	12	8.25	2.09
6	731	6.90	25.41	46	0.86	0.69
7	761	9.98	28.85	724	3.62	7.35
8	817	9.52	29.15	817	3.63	7.98
9	802	8.36	28.34	802	2.54	6.29
10	805	7.90	24.54	805	2.96	7.09
11	782	6.85	27.45	782	2.79	8.72
12	765	7.31	26.20	763	2.89	7.98

Table 10. US Wheat Average Daily Profit Cents/Bushel by WASDE Report Month

WASDE	Trade and Hold Model			Variable Position Model		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	798	-0.02	-0.12	771	-0.25	-1.35
2	669	0.26	1.38	636	-0.10	-0.53
3	688	0.31	1.06	695	-0.28	-1.01
4	199	0.38	0.79	0	.	.
5	0	.	.	0	.	.
6	614	-0.35	-1.60	3	-0.28	-0.11
7	760	0.31	1.18	645	0.05	0.21
8	839	0.20	0.87	752	0.07	0.34
9	801	0.45	2.19	801	0.16	0.81
10	803	0.56	2.75	803	-0.12	-0.59
11	798	0.10	0.58	777	0.04	0.23
12	763	-0.16	-0.90	784	0.08	0.42

Table 11. US Wheat Average Daily Profit Cents/Bushel by WASDE Report Month for Total Market Movement and Perfect Foresight

WASDE	Trade and Hold Model			Variable Position Model		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	798	3.58	22.08	771	0.66	3.55
2	669	3.74	19.41	636	1.46	7.63
3	688	4.68	13.35	695	1.09	3.94
4	199	4.08	6.88	3	-0.28	-0.11
5	0	.	.	0	.	.
6	614	4.20	19.84	0	.	.
7	760	4.91	21.88	645	1.64	6.79
8	839	4.65	23.67	752	1.32	6.31
9	801	4.37	23.41	801	1.39	7.07
10	803	4.32	21.87	803	1.48	7.47
11	798	3.90	22.06	777	1.26	7.26
12	763	3.80	21.54	784	1.15	5.98

Table 12. US Corn Average Daily Profit Cents/Bushel by Days Until Report for Rolling Regression Model

Days Until Report	Ending Stocks 24 Months Profit	Ending Stocks 24 Months t-Value	Predicted Yield 24 Months Profit	Predicted Yield 24 Months t-Value
0	0.56	1.75	0.60	1.68
1	-0.15	-0.67	-0.19	-0.86
2	0.05	0.20	-0.09	-0.40
3	-0.02	-0.09	-0.13	-0.49
4	-0.28	-0.94	-0.03	-0.09
5	0.32	1.17	0.21	0.77
6	0.12	0.55	0.23	0.95
7	0.48	2.19	0.04	0.16
8	0.36	1.54	0.55	2.30
9	0.48	1.50	0.45	1.35
10	0.23	0.80	0.09	0.28
11	0.25	0.75	0.29	0.83
12	0.34	0.95	0.09	0.23
13	0.14	0.68	0.16	0.77
14	0.16	0.76	-0.02	-0.08
15	0.16	0.73	-0.19	-0.84
16	-0.13	-0.47	0.09	0.33
17	0.34	1.26	-0.04	-0.14
18	-0.25	-0.96	-0.03	-0.10
19	-0.19	-0.75	-0.21	-0.73
20	0.60	2.37	0.21	0.74
21	0.24	1.10	0.29	1.29
22	0.11	0.42	0.18	0.69
23	-0.47	-1.76	-0.46	-1.82
24	0.28	0.86	0.42	1.33
25	0.29	0.93	0.37	1.16
26	0.26	0.89	-0.27	-0.87
27	0.20	0.84	0.24	1.01
28	0.22	0.74	-0.26	-1.02
29	-0.09	-0.22	0.48	1.27
30	0.49	0.50	0.24	0.31
31	0.18	0.64	0.00	0.00

Table 13. US Soybeans Average Daily Profit Cents/Bushel by Days Until Report for Rolling Regression Model

Days Until Report	Ending Stocks 36 Months Profit	t-Value	Predicted Yield 60 Months Profit	t-Value
0	0.22	0.28	0.18	0.22
1	-0.92	-1.45	-1.14	-2.10
2	0.86	1.37	0.19	0.36
3	-1.75	-2.24	-1.01	-1.34
4	1.78	2.00	1.09	1.18
5	2.72	3.59	0.92	1.23
6	-0.38	-0.63	0.22	0.38
7	0.25	0.42	-0.12	-0.20
8	0.35	0.56	0.43	0.71
9	-0.81	-0.99	-1.29	-1.69
10	0.43	0.55	0.08	0.11
11	-0.18	-0.22	-0.23	-0.26
12	-0.67	-0.74	-0.57	-0.61
13	1.11	1.72	2.29	3.69
14	0.59	1.10	0.12	0.23
15	0.47	0.74	-0.27	-0.45
16	0.47	0.60	0.03	0.04
17	-0.01	-0.01	0.04	0.05
18	0.52	0.68	-0.37	-0.50
19	0.37	0.52	-0.62	-0.78
20	0.22	0.36	0.11	0.17
21	0.23	0.40	0.05	0.09
22	0.63	0.93	-0.12	-0.18
23	-0.62	-0.90	0.12	0.19
24	0.32	0.38	-0.78	-0.94
25	0.28	0.34	-1.99	-2.26
26	0.66	0.83	0.78	0.90
27	1.36	2.42	0.56	0.92
28	-0.25	-0.37	-0.61	-0.89
29	0.49	0.64	0.23	0.27
30	-1.25	-0.70	-0.55	-0.31
31	-2.32	-1.40	-1.99	-1.14

Table 14. US Wheat Average Daily Profit Cents/Bushel by Days Until Report for Rolling Regression Model

Days Until Report	Ending Stocks 60 Months Profit	t-Value	Predicted Yield 12 Months Profit	t-Value
0	0.23	0.79	-0.39	-1.07
1	-0.12	-0.45	-0.02	-0.05
2	0.21	0.74	-0.14	-0.45
3	-0.47	-1.49	-0.60	-1.88
4	-0.04	-0.11	0.05	0.12
5	0.40	1.19	-0.23	-0.63
6	-0.31	-1.14	0.50	1.60
7	0.32	1.13	-0.29	-0.95
8	0.02	0.07	-0.30	-1.00
9	-0.24	-0.70	0.49	1.44
10	0.17	0.53	-0.07	-0.19
11	-0.08	-0.21	-0.11	-0.28
12	0.38	0.72	0.97	1.64
13	0.13	0.50	0.71	2.93
14	0.42	1.61	0.22	0.84
15	0.01	0.02	-0.55	-1.25
16	-0.09	-0.26	-0.27	-0.78
17	-0.20	-0.69	-0.04	-0.13
18	-0.14	-0.50	-0.02	-0.05
19	-0.50	-1.64	-0.08	-0.23
20	0.12	0.52	0.13	0.48
21	-0.24	-1.03	-0.16	-0.64
22	0.52	1.57	0.37	1.15
23	0.19	0.58	0.53	1.72
24	0.22	0.65	0.20	0.63
25	-0.35	-1.21	0.50	1.58
26	0.14	0.39	0.08	0.21
27	0.07	0.27	0.20	0.87
28	0.01	0.05	0.15	0.48
29	0.85	2.13	-0.02	-0.05
30	0.19	0.21	0.71	0.81
31	-0.20	-0.37	-1.79	-2.06

Table 15. US Corn Average Daily Profit Cents/Bushel by WASDE Report Month for Rolling Regression Model

WASDE	Ending Stocks 24 Months			Predicted Yield 24 Months		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	731	-0.04	-0.40	731	-0.15	-1.38
2	659	0.34	2.29	659	0.17	1.19
3	604	0.07	0.46	604	-0.14	-0.98
4	21	0.29	0.60	0	.	.
5	43	0.71	1.56	0	.	.
6	655	0.13	0.86	395	0.29	1.21
7	682	0.28	1.26	416	0.02	0.07
8	794	-0.17	-0.99	550	0.39	1.81
9	759	0.37	2.47	748	0.42	2.78
10	762	0.31	1.94	762	0.21	1.4
11	757	0.30	2.17	757	0.06	0.45
12	741	0.12	0.92	741	-0.12	-0.92

Table 16. US Corn Average Daily Profit Cents/Bushel by WASDE Report Month for Rolling Regression Model Under Perfect Foresight

WASDE	Ending Stocks 24 Months			Predicted Yield 24 Months		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	731	0.46	4.40	731	0.51	4.97
2	659	0.95	6.71	659	0.94	6.87
3	604	0.90	6.20	604	0.85	6.30
4	21	0.48	1.02	0	.	.
5	43	0.70	1.52	0	.	.
6	655	0.97	6.58	395	1.18	5.01
7	682	1.46	6.75	416	1.41	4.62
8	794	1.44	8.52	550	1.28	6.14
9	759	1.11	7.69	748	1.14	7.97
10	762	1.06	6.78	762	1.04	7.11
11	757	0.92	6.95	757	0.94	7.37
12	741	0.92	7.28	741	0.88	7.30

Table 17. US Soybean Average Daily Profit Cents/Bushel by WASDE Report Month for Rolling Regression Model

WASDE	Ending Stocks 36 Months			Predicted Yield 60 Months		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	687	0.09	0.28	643	-0.09	-0.28
2	646	0.55	1.42	616	0.42	1.21
3	642	-0.12	-0.30	586	-0.77	-2.10
4	0	.	.	0	.	.
5	17	0.57	0.31	0	.	.
6	658	-0.15	-0.39	375	-0.75	-1.40
7	682	0.65	1.27	395	-1.10	-1.69
8	750	-0.46	-0.98	445	-0.87	-1.56
9	718	0.77	1.83	640	1.36	3.19
10	718	0.27	0.64	654	-0.34	-0.86
11	701	0.45	1.32	639	0.09	0.29
12	699	0.38	1.03	640	-0.04	-0.10

Table 18. US Soybean Average Daily Profit Cents/Bushel by WASDE Report Month for Rolling Regression Model Under Perfect Foresight

WASDE	Ending Stocks 36 Months			Predicted Yield 60 Months		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	687	1.72	5.30	643	1.52	5.03
2	646	2.65	7.13	616	2.05	6.07
3	642	3.12	8.02	586	2.58	7.22
4	0	.	.	0	.	.
5	17	0.57	0.31	0	.	.
6	658	2.51	6.86	375	2.84	5.52
7	682	3.22	6.44	395	3.77	6.00
8	750	3.16	6.95	445	3.09	5.69
9	718	2.53	6.15	640	2.29	5.45
10	718	2.67	6.54	654	2.35	5.99
11	701	2.80	8.50	639	2.54	8.22
12	699	2.88	8.05	640	2.49	7.48

Table 19. US Wheat Average Daily Profit Cents/Bushel by WASDE Report Month for Rolling Regression Model

WASDE	Ending Stocks 60 Months			Predicted Yield 12 Months		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	622	0.08	0.60	748	0.06	0.39
2	598	0.10	0.60	636	-0.33	-1.84
3	566	-0.14	-0.55	653	-0.25	-1.02
4	0	.	.	3	-0.31	-0.13
5	0	.	.	0	.	.
6	623	-0.52	-2.70	415	0.77	2.32
7	624	0.24	1.08	457	0.85	2.62
8	685	0.02	0.13	556	0.03	0.11
9	651	0.53	2.86	758	0.1	0.59
10	653	-0.04	-0.23	760	0.13	0.82
11	658	0.06	0.36	757	0.16	1.06
12	642	0.20	1.35	742	-0.2	-1.31

Table 20. US Wheat Average Daily Profit Cents/Bushel by WASDE Report Month for Rolling Regression Model Under Perfect Foresight

WASDE	Ending Stocks 60 Months			Predicted Yield 12 Months		
Month	N Obs	Profit	t-Value	N Obs	Profit	t-Value
1	622	0.75	5.17	748	0.91	6.32
2	598	1.12	6.87	636	1.32	7.61
3	566	1.36	5.17	653	1.30	5.22
4	0	.	.	3	-0.31	-0.13
5	0	.	.	0	.	.
6	623	1.39	7.24	415	1.38	4.16
7	624	1.64	7.50	457	1.88	5.87
8	685	1.30	6.99	556	1.16	4.77
9	651	1.55	8.51	758	1.20	7.32
10	653	1.14	6.68	760	1.02	6.36
11	658	0.83	5.22	757	1.07	6.97
12	642	0.98	6.37	742	1.19	7.74

Figure 1. **US Corn Final Intercept Coefficient for WASDE Projection Year Variable Position Model**

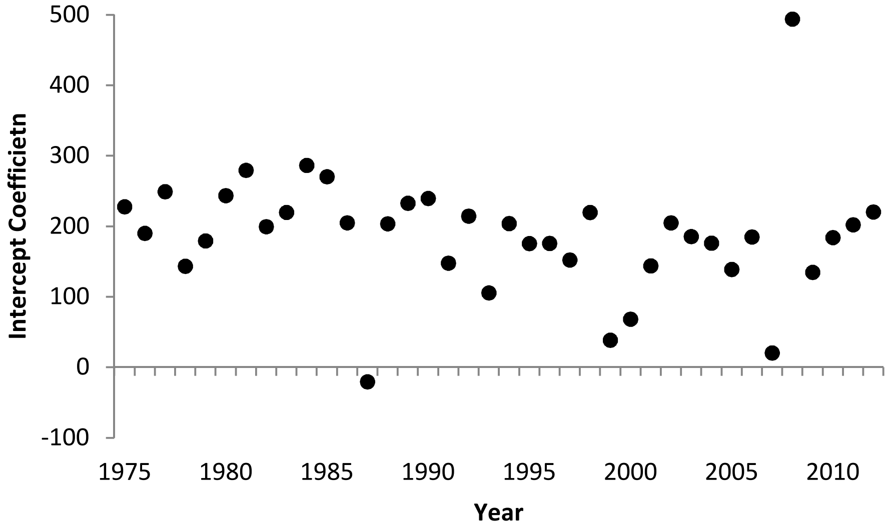


Figure 2. **US Corn Final Slope Coefficient for WASDE Projection Year Variable Position Model**

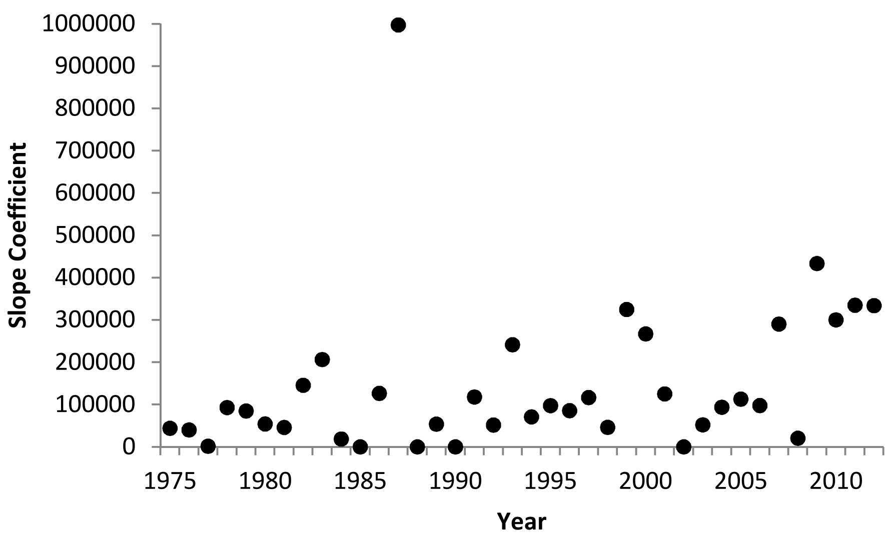


Figure 3. US Soybeans Final Intercept Coefficient of WASDE Projection Year Variable Position Model

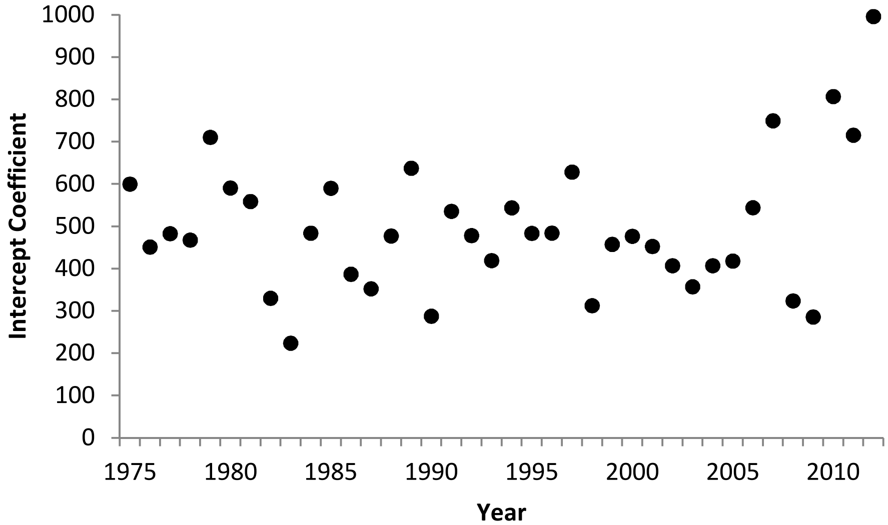


Figure 4. US Soybeans Final Slope Coefficient of WASDE Projection Year Variable Position Model

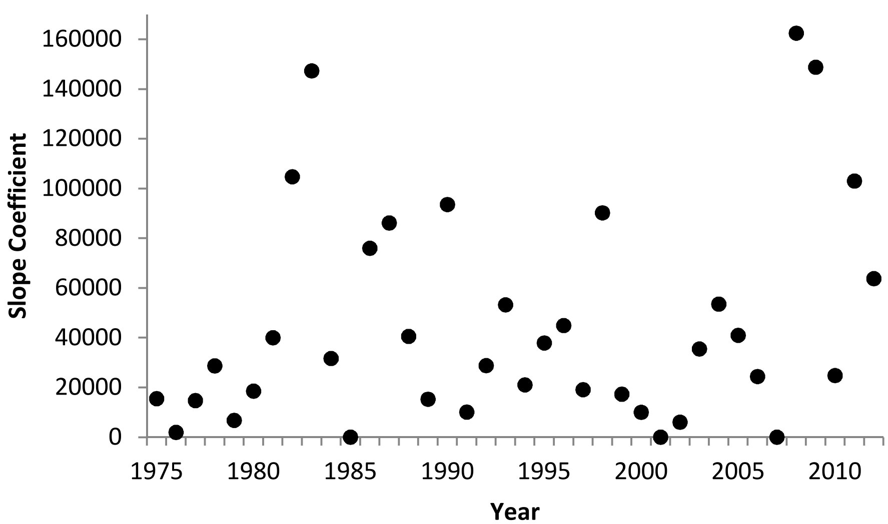


Figure 5. US Wheat Final Intercept Coefficient for WASDE Projection Year Variable Position Model

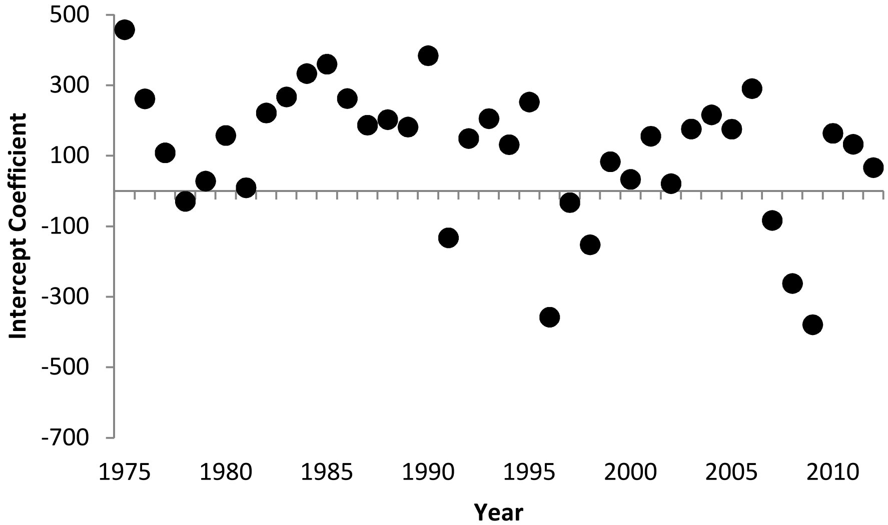


Figure 6. US Wheat Final Wheat Slope Coefficient for WASDE Projection Year Variable Position Model

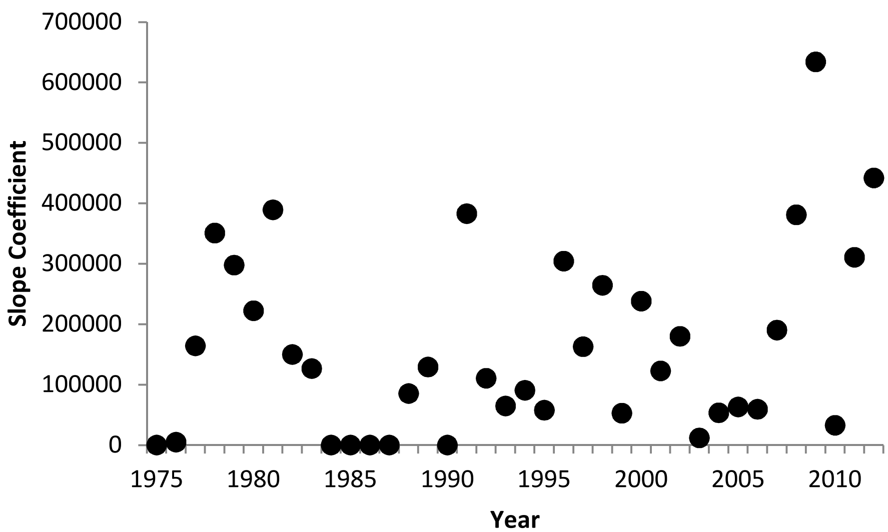


Figure 7. US Wheat Final Corn Slope Coefficient for WASDE Projection Year Variable Position Model

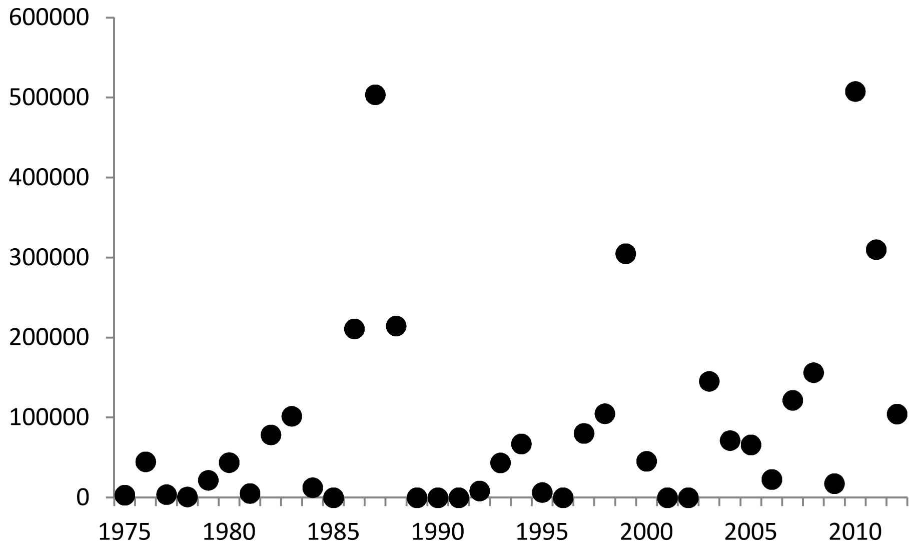


Figure 8. US Corn Average Daily Profit Cents/Bu. for Trade and Hold Model by Year

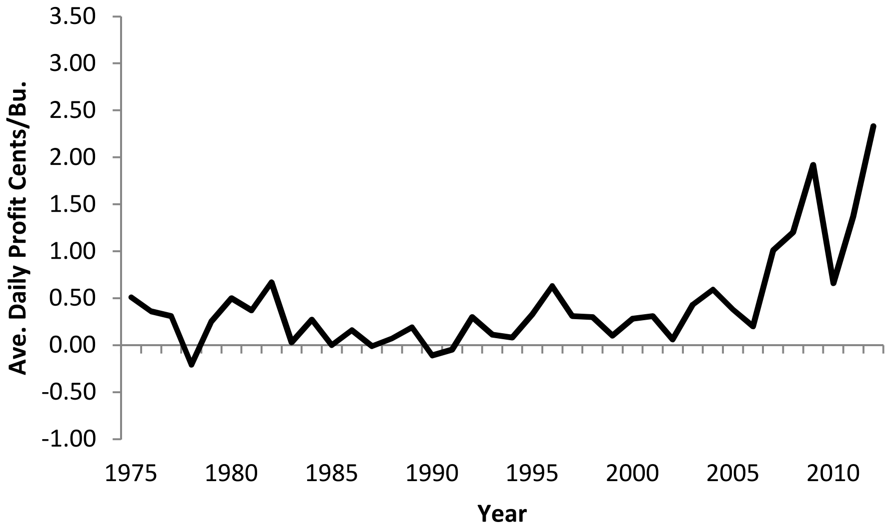


Figure 9. US Corn Average Daily Profit Cents/Bu. for Variable Position Model by Year

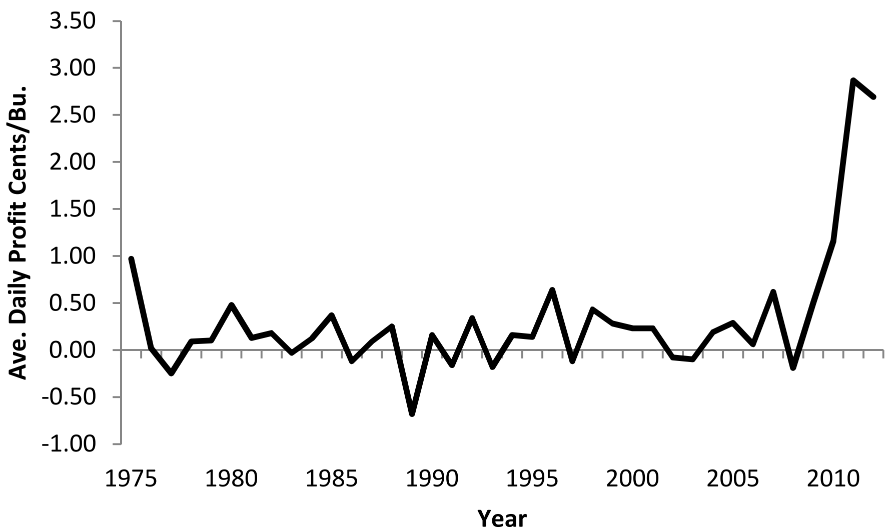


Figure 10. US Soybeans Average Daily Profit Cents/Bu. for Trade and Hold Model by Year

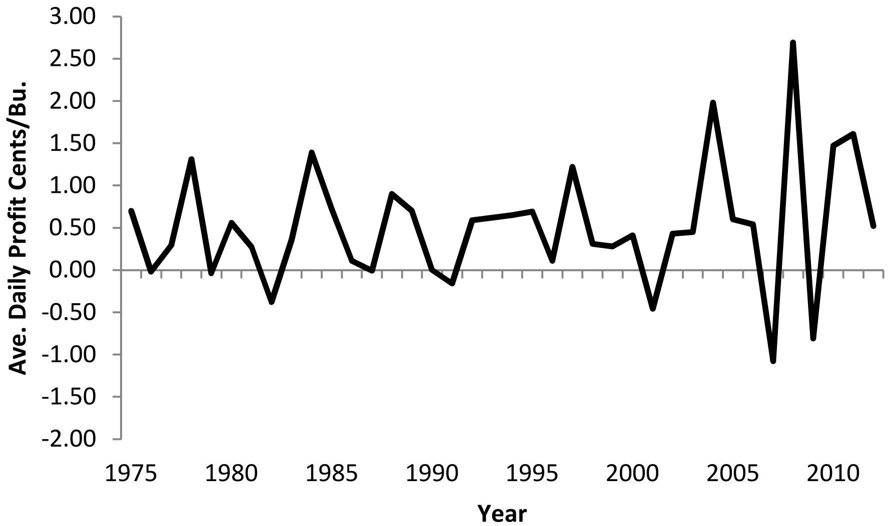


Figure 11. US Soybeans Average Daily Profit Cents/Bu. for Variable Position Model by Year

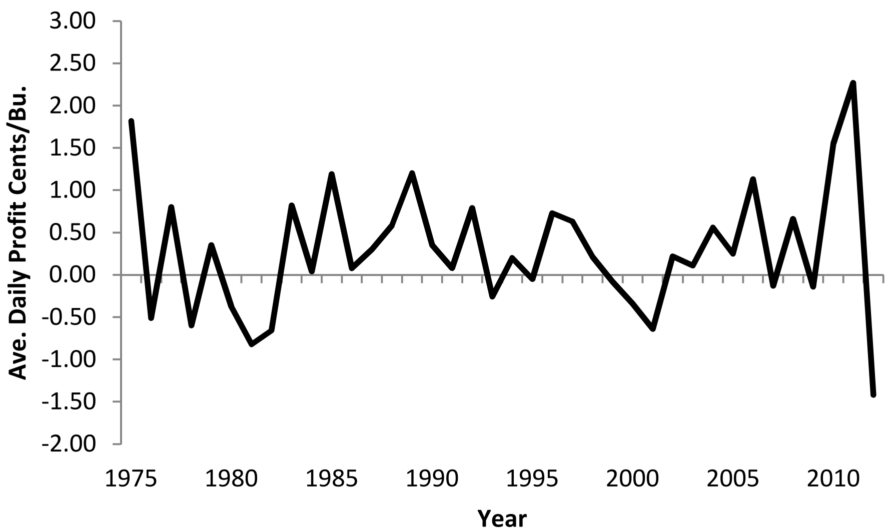


Figure 12. US Wheat Average Daily Profit Cents/Bu. for Trade and Hold Model by Year

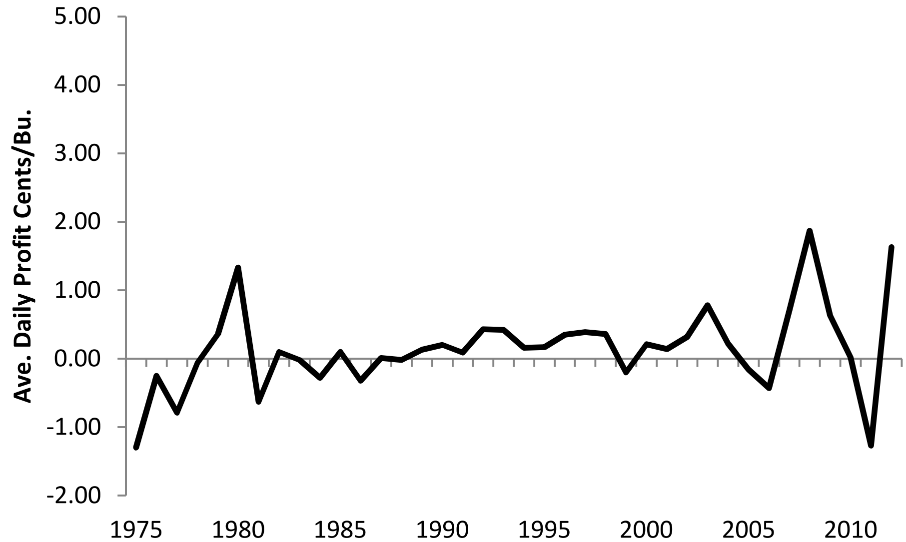


Figure 13. US Wheat Average Daily Profit Cents/Bu. for Variable Position Model by Year

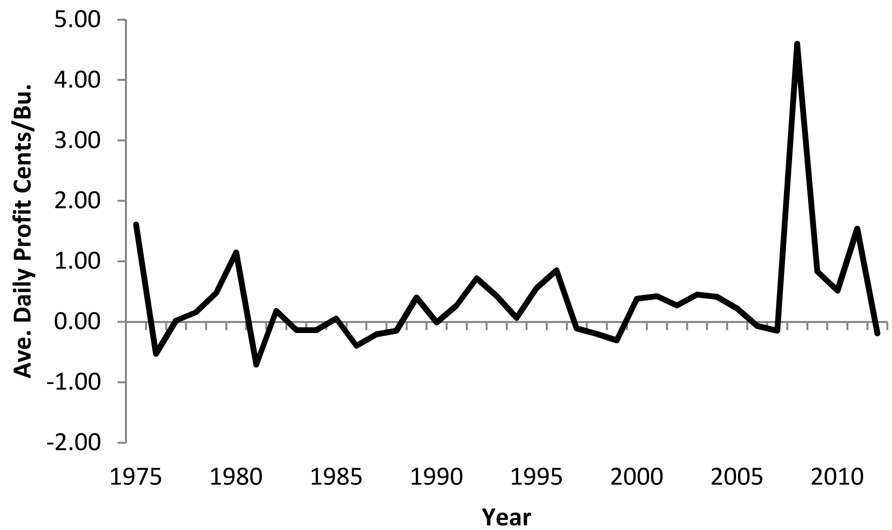


Figure 14. US Corn Daily Profit for Variable Position Model from Nonparametric Regression

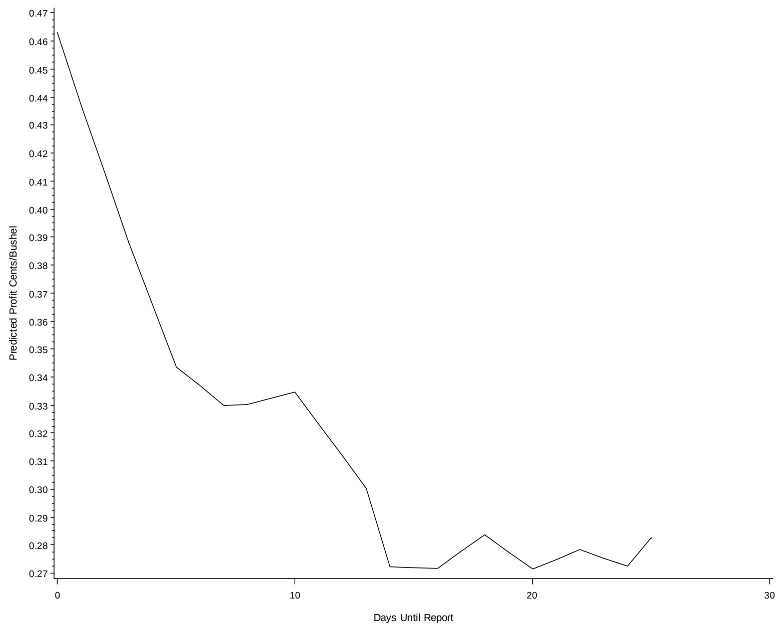


Figure 15. US Soybean Daily Profit for Variable Position Model from Nonparametric Regression

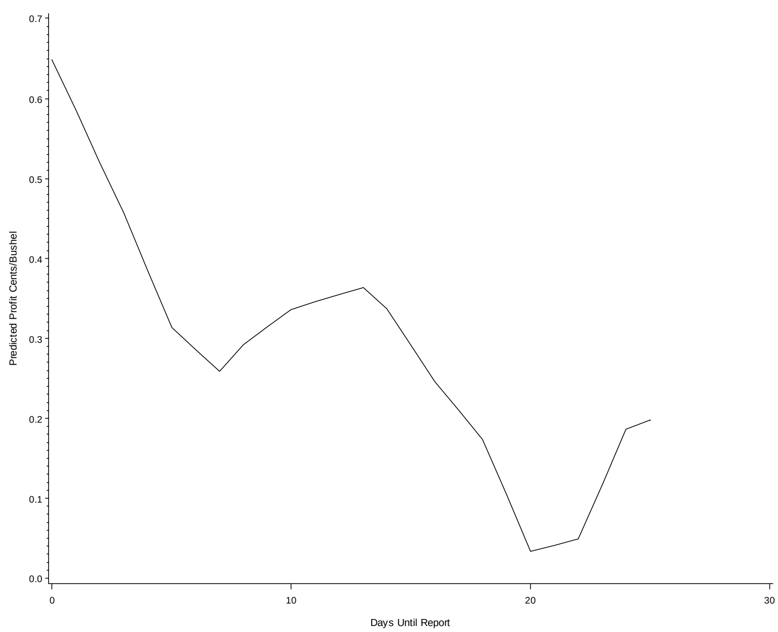
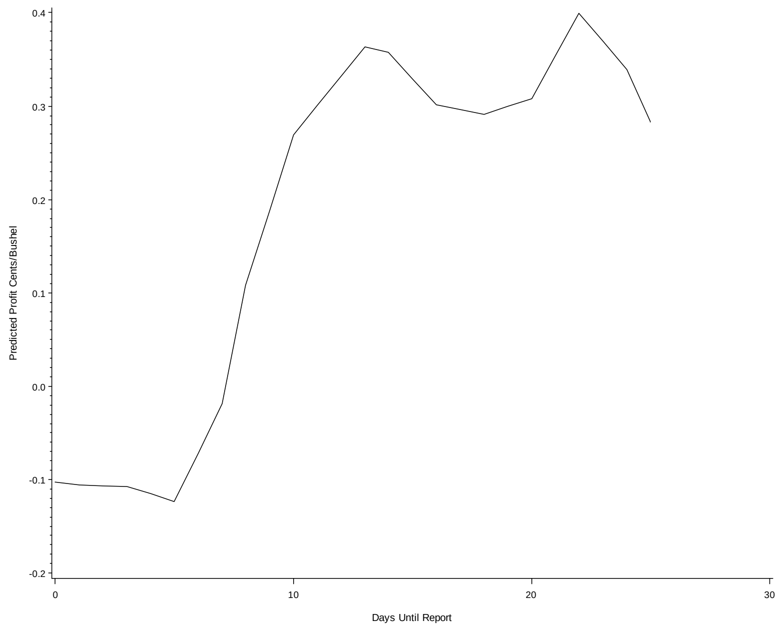


Figure 16. US Wheat Profit for Variable Position Model from Nonparametric Regression



APPENDIX

Figure 17. US Corn Variable Position Model SAS Code

```
DM 'log; clear; output; clear;';
proc datasets library=work kill;
run;
quit;

data WasdeIML; set wasde.Us_Corn_no_corrections(drop=f29-f184);
if ending_stocks__total = . then delete;
if substr(marketing_year,1,1) = 1 then Cropyr=marketing_year;
if substr(marketing_year,1,1) = 2 then Cropyr=marketing_year;
retain Cropyr;
format date mmddyy.;
Year=substr(cropyr,6,2)*1;
if year lt 50 then year=2000+year;
else year=1900+year;
output;
proc sort; by year Date;
*sorts WasdeIML by year and date;

proc sort data=futprice.c_h out=Corniml; by year Date;
*creates a data set called CornIML and sorts by year and date;

data Corniml1; set Corniml;
if year lt 50 then year=2000+year;
else year=1900+year;
output;
proc sort; by year date;

data CornpriceIML;
merge CornIML1 WasdeIML; by year date;
if Ending_stocks__total=. then delete;
if close=. then delete;
proc sort; by year date;

data RegCornIML;
set CornpriceIML;
if year ne lag(year) then obs=1;
output;
obs=obs+1;
retain obs;
```

```
proc iml;
use RegCornIML var {close Ending_stocks__total obs year};
read all;
n=nrow(close);
forecast  = j(n,1,0);
storebeta = j(n,2,0);
lastprice = j(n,1,0);
nextprice = j(n,1,0);
beta = j(2,1,0);
beta[2,] = -.002;
do ii=1 to n;
if obs[ii,]=1 then oldbeta1=beta[1,];
if obs[ii,]=1 then oldbeta2=beta[2,];
if obs[ii,]>=2 then do;
x= j(obs[ii,],1,1) || 1/Ending_stocks__total[(ii-obs[ii,]+1):ii,];
y= close[(ii-obs[ii,]+1):ii,];
beta=ginv(x`*x)*x`*y;
if beta[2,] < 0 then beta[2,]=0;
if obs[ii,] <= 10 then beta[2,]=(obs[ii,]/10)*beta[2,]+(1-
obs[ii,]/10)*oldbeta2;
beta[1,]=y[obs[ii,],]-beta[2,]*x[obs[ii,],2];
if ii < n then do;
if (year[ii+1,] = year[ii,]) then do;
forecast[ii,] = beta[1,]+beta[2,] / Ending_stocks__total[ii+1,];
*forecast[ii,] = close[ii+1];
storebeta[ii,] = t(beta);
lastprice[ii,] = close[ii,];
nextprice[ii,] = close[ii+1,];
end;
end;
end;
end;
outdata=forecast || storebeta || lastprice || nextprice;
print outdata;
create predictiml from outdata [colname={"forecast" "beta0" "beta1"
"lastprice" "nextprice"}];
append from outdata;
close predictiml;
stop;


data predictiml1;
merge predictiml regcorniml;

data predictiml2;
merge predictiml1 corniml1;
by year date;
proc sort; by Date;

data CornPredict;
set predictiml2;
error=close-forecast;
if forecast=0 then delete;
proc sort;
by year date;
```

```
run;

proc gplot data=Cornpredict;
Title 'US Corn Close/Date Forecast/Date Error/Date';
symbol1 interpol=join
       value=point
       cv=red
         line=1;
symbol2 interpol=join
       value=point
       cv=green
         line=2;
symbol3 interpol=join
            value=point
            cv=blue
            line=3;
plot close*date
     forecast*date
     error*date
/ overlay legend;
run;

data cornplotbeta2; set predictiml1;
lagbeta0=lag(beta0);
lagbeta1=lag(beta1);
run;

data cornplotbeta1; set cornplotbeta2;
lagbeta0=lag(lagbeta0);
lagbeta1=lag(lagbeta1);
run;


data cornplotbeta; set cornplotbeta1;
if year ne lag(year) then olbeta0=lagbeta0;
if year ne lag(year) then olbeta1=lagbeta1;
betayear=lag(year);
run;

proc gplot data=cornplotbeta;
Title 'US Corn Final Intercept Coefficient per Year';
symbol1 interpol=join
            value=point
            cv=black
            line=1;
plot oldbeta0*date
/overlay legend;
run;

proc gplot data=cornplotbeta;
Title 'US Corn Last Slope Coefficient For Every Year';
symbol1 interpol=join
            value=point
            cv=black
            line=1;
```

```
plot oldbeta1*date
/overlay legend;
run;

data Cornprofiml;
set Cornpredict;
by year date;
if close = . then delete;
*deletes data without a close number;
if forecast ne . then price_forecast=forecast;
if price_forecast = . then price_forecast=lag(price_forecast);
if year ne lag(year) then price_forecast = .;
retain price_forecast;
position=(-1)**(price_forecast<close);
if year ne lag(year) then position= .;
*prevents trade across contract years;
run;

data Cornprice;
set Cornprofiml;
format Next_Date mmddyy.;
if position ne . then Buysell=Position;
closedif=dif(close);
if Next_Report_Date ne . then Next_Date=Next_Report_Date;
retain Next_Date;
days=Next_Date-date;
if price_forecast = 0 then buysell=.;
proc sort; by year date;

data Profit; set Cornprice;
by year date;
month=month(next_date);
if price_forecast > close then buysell = 1;
else buysell = -1;
if price_forecast = . then buysell = .;
lagbuysell = lag(buysell);
profit=closedif*lagbuysell;
if lag(next_date)ne next_date then do;
days=0;
end;
run;

data CornProfitFinal; set Profit;
if price_forecast=. then delete;
if profit = . then delete;
if days > 31 then delete;
if days < 0 then delete;
lagdays=lag(days);
if lagdays=days then profit=.;
proc sort; by year date;
run;

proc reg;
model profit= ;
output r=resid out=cornprofitfinal;
```

```
data cornprofitfinal; set cornprofitfinal;
E2=log(resid*resid);
proc reg;
model E2=year;
output p=ehat out=cornprofitfinal;
data cornprofitfinal; set cornprofitfinal;
WT=1/exp(Ehat);
run;

proc means mean sum std min max t probt maxdec=2 fw=6;
Title "Average Corn Trade and Hold Model Daily Profit";
Title2 "Variable Profit";
var Profit;
weight wt;
run;

proc means mean sum std min max t probt maxdec=2 fw=6;
Title3 "Class=Days Til Report";
var Profit;
class days ;
weight wt;
run;

proc means mean sum std min max t probt maxdec=2 fw=6;
Title3 "Class=Month";
class month;
var profit;
weight wt;
run;

proc means mean sum std min max t probt maxdec=2 fw=6;
Title3 "Class=Year";
class year;
var profit;
weight wt;
run;


data Test;
set cornprofitfinal;
m=month(date);
run;

*///////////////////////////////////////*
Proc GAM procedure to graph smoothed
profit on days till report release
*\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\*;

ODS GRAPHICS ON;
PROC GAM DATA = CornProfitFinal;
MODEL profit = loess(days,DF=3);
OUTPUT OUT = CornProfitperday PRED ADIAG;
RUN;

PROC SORT DATA=CornProfitperday(KEEP=Profit days p_profit p_days)
```

```
      OUT=PPD;
BY Days;
DATA PLOT; MERGE PPD;
if days > 25 then delete;
PROC STANDARD M=0 S=1 DATA=PLOT OUT=PLOT;
VAR profit;RUN;
LEGEND1 FRAME CFRAME=WHITE CBORDER=NONE LABEL=NONE POSITION=CENTER;
AXIS1 LABEL=(ANGLE=90 ROTATE=0 "Profit Cents/Bushel");
AXIS2 MINOR=NONE LABEL=("Days Until Report");
SYMBOL1 COLOR=BLACK INTERPOL=JOIN VALUE=NONE LINE=1;
PROC GPLOT DATA=PLOT;
TITLE 'US Corn Daily Profit';
PLOT p_profit*days =1/OVERLAY nolegend noframe
CFRAME=WHITE VAXIS=AXIS1 HAXIS=AXIS2;

run;

quit;
```

VITA

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