IMPACT OF SEASONALITY ON AGRICULTURAL COMMODITY PRICE BEHAVIOR

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Impact of Seasonality on Agricultural Commodity Price Behavior

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ABSTRACT

United States is the world's largest producer of corn, accounting for 39% of total corn produced. Soybeans is the second largest crop in cash sales, and the number one export crop in the U.S., accounting for 27% of the world's soybean production. Wheat ranks third among the U.S. field crops in both planted acreage and gross farm receipts. The objective of this study is to forecast corn, soybean and wheat prices using time series regression model with seasonal dummies, autoregressive models and monthly price index and also to understand the relationship between exchange rate and commodity prices. Twenty three years of monthly data starting from 1991 to 2013, obtained from National Agricultural Statistics Service, USDA, were used in this study to forecast commodity prices. Results reveal that forecasted corn prices for 2014 range from $4.74 to $5.013, while soybean prices for the same time period range from $11.085 to $11.803 and wheat prices range from $6.14 to $6.58 and the results are on par with actual prices. The outcome of this study can aid both growers and end users in making optimal production decisions and in managing overall price risk.

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CHAPTER I

INTRODUCTION

Corn (*Zea Mays*) a cereal crop, also known as maize, is native to South America and is grown widely in temperate and tropical regions with well drained and fertile soils. It grows in most parts of the world, but the leading producers of corn are: U.S., Brazil, European Union and China. These four countries together produce about 60% of the world's corn and U.S. is the largest producer of corn accounting for 39% of the world's corn. Corn is a summer annual crop in the United States and Canada, where the seeds are planted in the spring, the resulting plant grows during the summer, reproduces seed, and is harvested in the fall. The Pacific Rim region in Asia is the fastest emerging market for U.S. corn. The United States leads the world in per capita corn consumption. Corn is an important crop and staple food for more than 1.2 billion people in sub-Saharan Africa and Latin America. Corn efficiently converts solar energy into biomass and is also a large source of energy and nutrients for animal and human consumption. Corn planted over 80 million of acres of land in the United States, is mainly used as livestock feed and as raw material for industrial products like sweeteners, starch, corn oil, beverage, industrial alcohol, fuel ethanol. Nearly 40% of the corn produced in the U.S. is used for ethanol production, 36% is used for livestock feed, approximately 20% is exported, and the remaining crop is used in the food industry. Japan is the largest export market for U.S. corn with a 28% market share followed by Mexico with 19% and South Korea with a 13% market share. A relatively small percentage of corn production is used for food in the United States. There are 5 main endosperm types of corn grown in the US: pop, flint, flour, dent and sweet. Dent is the most vastly used variety, utilized for livestock feed, starch, syrup, oil and alcohol. Corn is

grown in most of the states in the U.S. but is mainly grow in Iowa, Illinois, Indiana, South Dakota, Nebraska, Kentucky, Ohio and Missouri. It is the most valuable agricultural product and accounts for more than a quarter of all farm receipts in the states of Iowa, Illinois, and Indiana the heart of the "corn belt"; it is among the top two or three farm products in many neighboring states (Capehart, 2011).The corn belt includes Iowa, Illinois, Nebraska, Minnesota, Indiana, Ohio, Wisconsin, South Dakota, Michigan, Missouri, Kansas and Kentucky. Corn production has centered in this region due to a favorable combination of weather conditions, soil quality, and ground water availability. Corn is the nation's biggest crop economically, outpacing both soybeans and wheat in production value, number of acres planted and overall water use and its total production value in recent years has surpassed that of both wheat and soybeans combined. Its estimated total value was approximately $67 billion in 2013/14 (Capehart, 2011). 90% of U.S. corn is grown with biotech seeds, mostly on stacked traits, meaning it is both herbicide-tolerant and insect-resistant. Stacked traits are becoming increasingly popular, and currently 71% of all corn planted in the U.S. contains stacked traits. U.S. corn yield about 140 to 160 bushels per acre.

Corn production has been gradually increased in recent years due to several factors such as improvements in technology (seed varieties, fertilizers, pesticides, and machinery), modern production practices (reduced tillage, irrigation, crop rotations, and pest management systems), the Federal Agriculture Improvement and Reform Act of 1996; which says that farmers can make their own decision on the most profitable crop for a given year, and finally the recent biofuel mandates. Between 2006 to 2011, crop area devoted to growing corn increased by more than 13 million acres due to demand for ethanol (Capehart, 2011).

In 2011, for the first time, amount of corn diverted to ethanol production surpassed the amount used as livestock feed. Ethanol boom will significantly increase the corn planted acreage in next two to ten years. Ethanol boom will likely help boost the rural economy of America as higher commodity prices will result in higher income to farmers. In coming years, 40% of corn grown in U.S. will be used to make ethanol, which will account for 70% of gasoline used across the nation. The agribusiness industry in the United States depends on corn for high fructose corn syrup. In recent times U.S. depends heavily on corn for ethanol, raw material for industry, and for export. This makes the corn price susceptible to volatility and the economy heavily dependent on corn production. Hence it is important to forecast corn prices and analyze production trends with in the country. Most of the farmers increased corn acreage by adopting a crop rotation practice between soybeans and corn, which caused the soybeans production to decrease. The production of soybeans has to increase in order to meet increased demand from China.

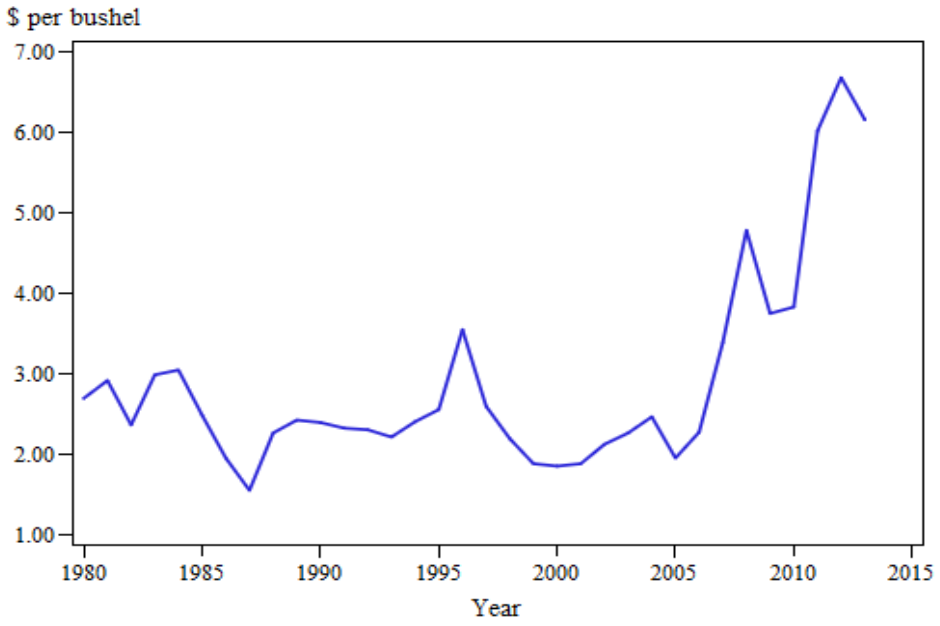

Figure 1: Yearly average U.S. corn price

Soybeans can be used as an oilseed as well as a pulse crop with the highest percentage of protein amongst all pulses. Soybeans are native to East Asia, and the cultivation was restricted to the Asian countries, until it was introduced to the United States in 1804. Cultivated primarily in warm and hot climates, soybeans were originally used as nitrogen fixers in the early systems of crop rotation. Soybeans are the dominant oilseed in the United States, accounting for about 90% of U.S. oilseed production and it is the second most planted crop after corn. More than 80% of U.S. soybeans acreage is concentrated in the upper Midwest, although significant amounts are still planted in the historically important areas of the Delta and the Southeast. Most U.S. soybeans are planted in May and early June and harvested in late September and October (Ash, 2011). The plant is susceptible to a number of bacterial diseases, including blight and wilt. Modern plants reach a height of about 1 meter, and take between 80 and 120 days from planting to harvest. Soybeans account for a 1/3rd of total oil produced in the world. It's an important food crop in the world which provides protein for millions of people and also used as an ingredient for many chemical products. Soybeans are produced globally but nearly 80% of production is concentrated in the United States, Brazil and Argentina. Soybean seed contains 17 % oil, 63% meal, 50% protein. Due to the protein content, it is consumed as soymilk in East Asia. Among the leguminous crops, soybean provides inexpensive and high quality protein when compared to meat, poultry and eggs. In some countries, soybeans are consumed directly as a food product for human consumption, but today most of the soybeans are used to obtain soybean oil and soybean meal, which improved the soybeans crop value. Soy cake which is a product from soybeans oil production is used as animal feed in many countries. Soybeans have also started being used in the production of biodiesel. Soybeans is a

dominant oilseed in the United States, accounting for about 90% of U.S. oilseed production. Soybeans is the second largest crop in cash sales and the number one export crop in the Unites States. China, Mexico, European Union and Japan are major the importers of soybeans from United States. Majority of the soybeans crop produced in the U.S. is processed into oil and meal. The U.S. accounts for approximately 27% of world's soybeans production. In the United States, soybeans is produced primarily in Iowa, Illinois, Minnesota, Indiana, Ohio, Nebraska, and Missouri. Soybean export to China is expected to increase in 2014 due to heavy rains and flooding in other soybeans producing countries. The U.S Department of Agriculture (USDA) expects China's soybeans import to increase by 16% compared to 2010 (Ash, 2011). Soybean played an important role in the US-China agricultural trade relations, accounting for more than 50% of export to China. USDA predicted that China will import 69 million ton of soybeans for 2013-14 compared to 59 million tons in 2012-13.

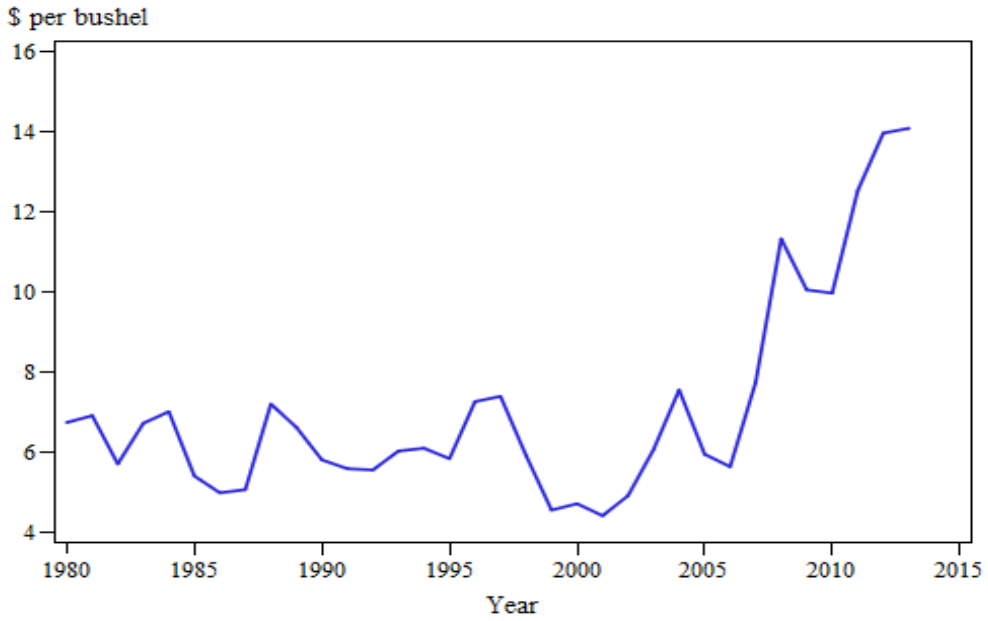

Figure 2: Yearly average U.S. soybean price

Wheat is the oldest domesticated plant and second-most produced crop on Earth. Wheat is believed to have originated in south-western Asia. Some of the earliest remains of the wheat have been found in Syria, Jordan, and Turkey. Primitive relatives of present day wheat have been discovered in some of the oldest excavations of the world in eastern Iraq, which date back 9,000 years. Other archeological findings show that bread wheat was grown in the Nile Valley about 5,000 B.C. as well as in India, China, and even England at about the same time. Wheat was first grown in the United States in 1602 on an island off the Massachusetts coast. Wheat is produced on about 215 million hectares worldwide, from the equator to latitudes of 60◦N and 44◦S. Approximately 630 million tons of straw are raised annually, approximately half in developing countries.

Wheat is produced throughout the world, but China has the largest land area devoted to wheat production, followed closely by the United States, India and the Russian Federation. Kazakhstan and Canada, ranking fifth and sixth, produce wheat on about half the area of the top four countries. In recent years, China with an average production of more than 100 million tons annually, ranks far ahead of the United States and India, each averaging about 60 million tons. Among the bigger land area producers, China's yield was 3.5 tons/ha, while the United States, India and Russian Federation produced 2.5, and 1.5 tons/ha, respectively. Wheat is the principal food grain and third largest field crop produced in the United States following corn and soybeans. The major wheat producing states are North Dakota, Kansas, Montana, South Dakota, Washington, and Idaho. Wheat varieties grown in the United States are classified as “winter wheat” or “spring wheat,” depending on the season when each is planted. The Winter wheat production represents 70-80% of total U.S. output. Winter wheat varieties are sown in the fall and usually become established before going

into dormancy when cold weather arrives. In the spring, plants resume growth and grow rapidly until summertime harvest. In the Northern Plains, where winters are harsh, spring wheat and durum wheat are planted in the spring and harvested in the late summer or fall of the same year. The five major classes of U.S. wheat are hard red winter, hard red spring, soft red winter, white, and durum. Hard red winter and hard red spring wheat account for 60% of wheat production. Each class has a somewhat different end use and production tends to be region-specific and half of the U. S. wheat crop is exported to sub-Saharan Africa, Japan, Mexico, and Philippines.

Although useful as a livestock feed, wheat is used mainly as a human food. It is nutritious, concentrated, easily stored and transported, and easily processed into various types of food. Unlike any other plant derived food, wheat contains gluten protein, which enables leavened dough to rise by forming minute gas cells that hold carbon dioxide during fermentation. This process produces light textured bread. Wheat supplies about 20% of the food calories for the world's people and is a national staple in many countries. In Eastern Europe and Russia, over 30% of the calories consumed come from wheat. The per capita consumption of wheat in the United States exceeds that of any other single food staple. Besides being a high carbohydrate food, wheat contains valuable protein, minerals, and vitamins. Wheat protein, when balanced by other foods that supply certain amino acids such as lysine, is an efficient source of protein. Wheat is a major ingredient in such foods as bread, porridge, crackers, biscuits, Muesli, pancakes, pies, pastries, cakes, cookies, muffins, rolls, doughnuts, gravy, boza (a fermented beverage), and breakfast cereals.

Despite rising global wheat trade, the U.S. share of the world wheat market has eroded in the past two decades due to various factors. A increased demand for corn, resulting from

increased ethanol production, has caused some wheat acreage in the Upper Midwest to be shifted to corn production. A second factor would be declining returns compared to other crops and changes in government programs for wheat farmers. Lastly U.S. wheat acreage is decreasing due to no genetic modification with respect to insects, disease, and weed control.

Wheat is bought and sold on a vigorous and complex world market. U.S. wheat can be purchased by anyone around the world through private companies. There are three key U.S. wheat markets, the Chicago Board of Trade, the Kansas City Board of Trade recently acquired by CME group and the Minneapolis Grain Exchange.

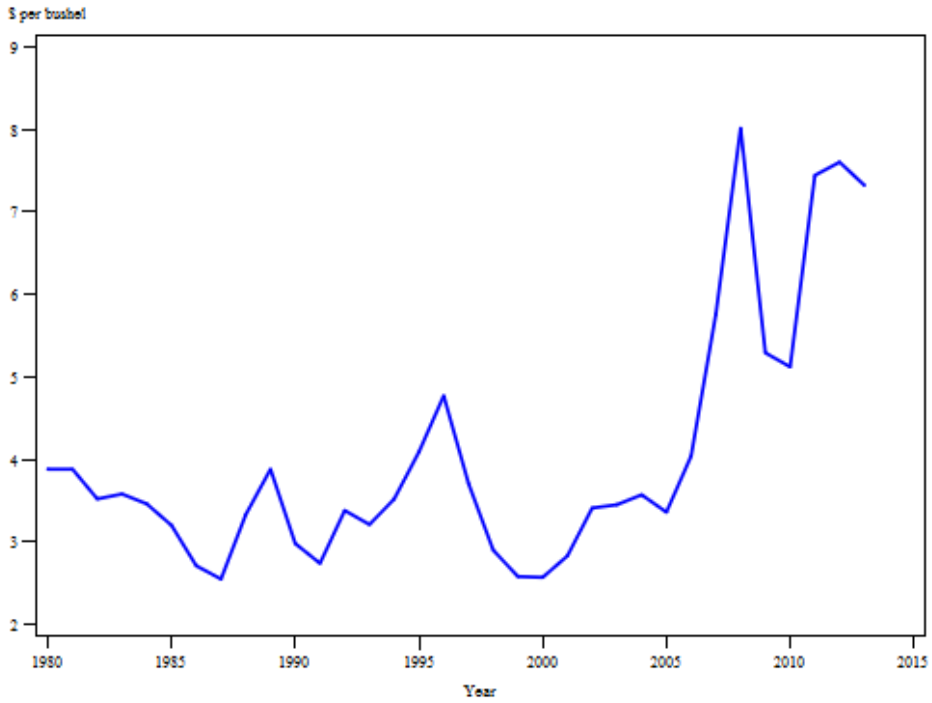

Figure 3: Yearly average U.S. wheat price

BACKGROUND SIGNIFICANCE

The production of many commodities is limited to a single crop year, while consumption occurs throughout the year, which results in recurring seasonal patterns of prices and quantities. Graphical analysis of monthly prices for most commodities show the lowest price at harvest, followed by a slow rise each month throughout the rest of year, followed by a decline just before the start of next year. This pattern normally repeats itself year after year. The rise in prices after harvest induces producers and processors to store part of the annual crop. And crop prices in the cash and futures markets are usually the lowest near harvest due to supply pressure. Conversely, prices are usually the highest near the end of the marketing year when supplies are less abundant.

Basic economic theory suggests that the behavior of agricultural commodity prices over time is governed by shifts in supply and demand. In particular, deviations of actual production from expected supplies can have a pronounced impact on seasonal price patterns. For most of the agricultural commodities, demand is more stable than supply. Systematic exogenous demand shifters such as population and demographic changes and disposable incomes, affect the demand for commodities (Ramirez, 2009). In recent years, corn, soybean and wheat prices are increasing due to ethanol production, more import demand from China and rise of global wheat trade, respectively. Supply numbers can be substantially volatile from year to year. During 2012, in the case of corn, soybeans, and wheat adverse climate effected the key producing regions such as midwestern U.S. Although it was short-lived, effects were large. This negative supply shock resulted in upward price spikes, impacting corn, soybean and wheat commodity markets. Seasonal price patterns can be used as a guide for developing a marketing plan when they are

examined along with supply and demand information and other marketing concepts. Seasonal price patterns can also be used to establish a time deadline for selling a portion of crop and also to formulate price objectives by considering potential storage costs.

Forecasts of price and production in commodity markets have been studied for almost a century. Forecasts use the past agriculture commodity prices to predict the future prices and this helps in determining the impact of new technology, time, and other economic factors on commodity production and prices. Forecasting of agricultural commodity prices reduces uncertainty surrounding agribusiness and helps predicate farmer's decisions. It is always important to forecast frequently and to look at anything that could effect the future hedgers and farmers marketing decisions. The ultimate reason for forecasting commodity prices is to put the farmers, hedgers and business managers in the best possible position relative to future market and business conditions. Unprecedented hikes and drops in corn, soybeans and wheat prices in recent years is a concern for both policy makers and general public. Farmers, policy makers, and traders are interested in forecasting prices to save on storage and production costs, develop optimal marketing decisions and to manage commodity price risk. The government, farmers, the industry and even players from the financial market are the main users of agricultural forecasts (Ribeiro and Oliveira, 2011). In recent times corn, soybeans, and wheat prices have risen by 50% compared to oil, metal, and energy prices. Fluctuation of corn, soybean and wheat prices during inflation periods makes commodities price forecasting important for emerging economies.

Prices of corn, soybeans and wheat are influenced by changing world and domestic factors which in turn determine supply and demand of these crops. As the U.S. is the largest producer of these crops, magnitude of production, pace of domestic consumption and level

of inventories are among the most important factors influencing the prices (Irwin et al., 2014). Market participants heavily depend on estimation and forecasts provided by public, private and research institutes. Forecast of corn, soybean and wheat prices help determine expected price, which in turn helps producers in evaluating decisions about grain storage, decide which crop should be replaced for next season, and plan annual cash flows and loan requests. Successful forward price contract negotiations can also be achieved by predicting future corn, soybean and wheat prices. Forecasted price information has become even more important for market participants due to changes in U.S agricultural policy.

The relationship between corn, soybean, wheat prices and exchange rates has attracted the attention of researchers and practitioners. Exchange rates help to predict the economic fundamentals including commodity prices (Engel and West, 2005). Huge fluctuations in commodity prices results in shocks to the economy of the country by significantly effecting commodity exports of the country.

Corn, soybeans and wheat prices increased significantly over the years due to increases in yield, acreage and by advancement of technology. There is also a concern, rising corn prices triggered unsustainable farming practices including the expansion of corn production into highly erodible and ecologically sensitive land (Sawyer and Barker, 2012). There has also been a dramatic shift away from the traditional annual rotation of corn and soybeans in favor of “continuous corn” (i.e. no rotation), which increases vulnerability to pests, and diminishes soil quality and long-term yields (USDA, natural resource conservation, 2013).

CHAPTER II

REVIEW OF LITERATURE

Previous research on commodity price forecasting involved wide range of techniques across time periods. A quick summary of important findings are briefly discussed below.

Jan et al. (2014), used three equation regression models to estimate determinates of nitrogen surplus and of its two components nitrogen intensity and nitrogen inefficiency at farm level in Swiss agriculture. Results show that the nitrogen surplus is dependent on farm characteristics like farm size, part-time farming, organic farming, and arable cropping. The farmer's age is found to negatively effect nitrogen surplus.

Baek and Koo (2009), studied the short and long-run effect of macroeconomic variables such as agricultural commodity prices, interest prices and exchange rates on the U.S. farm income using autoregressive distributed lag approach. Results reveal that commodity prices and interest rates have been significant factors in influencing U.S. farm income in both the short and long term. They also show that exchange rates play a crucial role in determining long-run behavior, but have little effect in the short term.

Kalkuhl (2014), analyzed how global commodity prices influence domestic food prices in developing countries using the autoregressive distributed lag model. Empirical analysis revealed that 90% of global poor live in countries where domestic food prices are influenced by international prices.

Al-Saad and Moosa (2005), investigated the nature of seasonality for monthly stock returns derived from a general index of the Kuwait Stock Exchange. The authors used time series model with stochastic dummies for analyzing data. The results reveal that seasonality is

present but it is deterministic as implied by the constancy of monthly seasonal factors over the sample period.

Sibel and Gulay (2012), studied increase in Turkish agriculture employment, post economic crisis of 2008. The authors used macroeconomic variables from 1988 to 2011 to search for agricultural employment increase and estimated parameters by using ordinary least square linear regression with post crisis and pre crisis analysis. Results state that agricultural price has significant positive relationship with agricultural employment for post economic crisis 2008, whereas it has negative relationship for the pre 2008 period when seasonal dummies are included.

Zhang and Buongiorno (2010), used the GARCH model and autoregressive distributed lag model to measure volatility of exchange rate and the effect of exchange rate on export quantity and price respectively. The study used data on United States export to 14 countries for eight commodity groups from January 1989 to November 2007. Results reveal that an increase in exchange rate variability of 1% led to a short run decrease in export quantity of 0.3-0.4% and to a short-run decrease in export price of 0.1% and with exchange rate level, exchange rate volatility may not be a major policy issue for US forest product exports.

Alam and Ahmed (2012), estimated aggregate export demand and exchange rate volatility for Pakistan, using autoregressive distributed lag model, for quarterly data from 1982-2008. The authors examined the long run as well as short run impact of real effective exchange rate volatility along with foreign income, relative price of exports and real effective exchange rate on demand for exports. Results show that real foreign income has a significant positive effect on export demand, suggesting that Pakistan's aggregate export

demand depends on its trading partner's income and relative price of exports may decrease the level of export demands in the long run.

Mehare and Edriss (2012), used autoregressive distributed lag model to find out the effect of exchange rate variability on export of oil seeds. For this study, data was collected from the National Bank of Ethiopia (NBE), Central Statistical Agency of Ethiopia (CSA), and Ethiopian Custom Authority (ECA). Results reveal that export oilseeds have negative relationship with exchange rate variability and export diversification. In this study authors suggested that the country should focus on improving trade and take advantage of policy changes.

Zheng et al. (2009), studied the effect of recent increase in grain prices due to ethanol production and its impact on feed cost and farm prices. This relationship was examined by using autoregressive distributed lag model (ARDL). Results show that 1% increase in corn prices caused 0.134% and 0.263% increase in feed prices in the short and long-run respectively and 1% increase in feed prices caused the catfish farm prices to increase by 0.106% in the short-run and by 0.211% in the long-run.

Orden (2002), examined the exchange rate effects on agricultural trade. In this paper, the author reviewed the relevant conceptual arguments, and summarized the evidence economists and agricultural economists have mentioned from 1970 to 1980, and also presented recent empirical analysis of exchange rate effects and briefly examined theconsequences of appreciation of the dollar on U.S. farm policy.

Agbolaa and Damoense (2003), used autocorrelation regression procedure for estimating demand functions for pulses, chickpeas and lentils in India for the period ranging from

1970 to 2000. Empirical results indicate that real GDP, population, urbanization, exchange rate and relative price are key determinants of import demand for pulses in India.

Musunuru (2013), investigated the presence of possible calendar anomalies, especially the month of the year effect in agricultural commodities. The GARCH models and non-linear models from the GARCH family, specifically TGARCH, EGARCH were used to examine volatility of agricultural commodities and to assess the role of asymmetries respectively. The results of the study reveal that agricultural commodities typically exhibit periods of high volatility stemming from both positive and negative shocks of new information.

Musunuru et al. (2013), forecasted the volatility of returns for corn futures using GARCH models and assessed, analyzed the time varying volatility of corn futures using non-linear models from the GARCH family, specifically TGARCH and EGARCH. Results of this study reveal that the EGARCH model provides the best sample forecast for corn and the leverage effect for corn is statistically significant indicating negative shocks have more impact on volatility than positive shocks.

Diersen (2008), forecasted hay price in South Dakota, using a balance sheet model. In this study several structural relations and equations were used to forecast acres, supply, and prices. The researcher in this study found out how to update the price forecast as additional information is obtained and also suggested extending the model to other states.

Ramirez and Fadiga (2003), forecasted U.S. soybean, sorghum, and wheat prices using asymmetric-Error GARCH models. Results reveal that the asymmetric-Error GARCH model proposed and illustrated in this study represents an improved alternative for the forecasting of time-series variables and for producing reliable confidence intervals for

these forecasts when the conditional probability distribution of the dependent variable is asymmetric.

CHAPTER III

RESEARCH METHODS

This study attempts to forecast corn, soybeans and wheat monthly prices and understand the relationship between exchange rate and commodity prices. Forecast methods range from unsophisticated approaches to large complex models. It is important to use forecasting techniques based on the data. Forecasting methods normally rely heavily on the assumption that what influenced things in the past will continue to influence them in the same way in the future-no changes will occur in fundamentals of the situation such as new technology, changes in consumer tastes and preferences, changes in government policies, world events, and so on. For this study monthly corn, soybean and wheat prices and real monthly commodity exchange rates data were obtained from the National Agricultural Statistics Service (NASS), USDA, for a period of 23 years ranging from 1991 to 2013. Forecasting techniques like regression model with seasonal dummies, autoregressive models and monthly price index are used to analyze the data.

Regression model

Regression analysis is one of the most commonly used tools in econometrics. It is concerned with describing and evaluating the relationship between a given variable called explained or dependent variable and one or more other variables called explanatory or independent variable.

Explained variable is denoted by y and the explanatory variables by , x_1,x_2,…..,x_k.If $k = 1$,there is only one of x variables, then it is known as **simple regression**. If $k > 1$,that is there are more than one x variables it is known as **multiple regression.**

The multiple regression equation is given by

$y_{i=}\alpha + \beta_1 x_{1i} + \beta_2 x_{2i}$+……+$\beta_k x_{ki}$+$\mu_i$ i=1, 2,……,n

n observations on k explanatory variables $x_{1,}x_{2,}\ldots,x_k$ and response variable y. Our goal is to study or predict the behavior of y for the given set of the explanatory variables. The errors μ_i are measurement errors in y and errors in the specification of the relationship between y and x's.

Multiple regression model assumes that

- repeated y responses are **independent** of each other
- y has a **constant variance** for any combination of the predictors
- Distribution of y for any fixed set of values for the explanatory variables follows a **normal distribution**

To incorporate the effect of seasonality on commodity price behavior, this study uses dummy variables. A dummy variable or indicator variable is an artificial variable created to represent an attribute with two or more distinct categories in regression analysis. It takes the value of 0 or 1 to indicate the absence or presence of some categorical effect that may be expected to shift the outcome. Dummy variables, also called as explanatory variables, are the proxy variables in regression models. In regression analysis, the dependent variables may be influenced not only by quantitative variables, but also by qualitative variables. A dummy independent variable, which for some observations has a value of 0 will cause that variable's coefficient to have no role in influencing the dependent variable, while when the dummy takes on a value 1, its coefficient acts to alter the intercept. The reason for including the dummy variable in the regression model is to account for the

response variable, by making the errors smaller and also to avoid a biased assessment of the impact of an explanatory variable, as a consequence of omitting other explanatory variables related to it. Dummy variable is frequently used in time series analysis, seasonal analysis, economic forecasting, biomedical studies, credit scoring, response modelling and so on. Dummy explanatory variables are used in regression analysis to

- allow for differences in intercept terms
- allow for differences in slopes
- estimate equations with cross-equation restrictions
- test for stability of regression coefficients

In this research we are dealing with time series data by including a time trend and also incorporating seasonality into the regression model by including a set of seasonal dummies. The first 11 variables are monthly dummy variables. The dummy variable describes every possible outcome, hence one of them must be excluded. Here there are 12 months, so we must exclude the dummy variable for one month. For this study, December has, been chosen to be excluded.

For a yearly time trend, each year trend variable increases by one unit. Time trend is constructed in such a way that 1991 equals to 1, 1992 to 2 … and 2013 to 23.

Monthly dummy variables and the time trend variable is constructed in Excel, using the regression tool to estimate a regression; with corn, soybeans and wheat prices as dependent variable and the monthly variable and year variable as explanatory variables.

The following regression model is used for predicting corn, soybean and wheat monthly prices.

Predicted corn price (C_t) =

$$\beta_1\theta_1+\beta_2\theta_2+\beta_3\theta_3+\beta_4\theta_4+\beta_5\theta_5+\beta_6\theta_6+\beta_7\theta_7+\beta_8\theta_8+\beta_9\theta_9+\beta_{10}\theta_{10}+\beta_{11}\theta_{11}+\beta_{12}(Y_t)+\epsilon_t \quad (1)$$

Predicated Soybean price (S_t) =

$$\beta_1\sigma_1+\beta_2\sigma_2+\beta_3\sigma_3+\beta_4\sigma_4+\beta_5\sigma_5+\beta_6\sigma_6+\beta_7\sigma_7+\beta_8\sigma_8+\beta_9\sigma_9+\beta_{10}\sigma_{10}+\beta_{11}\sigma_{11}+\beta_{12}(Y_t)+\epsilon_t \quad (2)$$

Predicted Wheat price (W_t) =

$$\beta_1\mu_1+\beta_2\mu_2+\beta_3\mu_3+\beta_4\mu_4+\beta_5\mu_5+\beta_6\mu_6+\beta_7\mu_7+\beta_8\mu_8+\beta_9\mu_9+\beta_{10}\mu_9+\beta_{11}\mu_{11}+\beta_{12}(Y_t)+\epsilon_t \quad (3)$$

Where β_1……..β_{12} are regression coefficients

θ_1…….θ_{11}, σ_1……σ_{11} ,and μ_1……$\mu_{11}$are monthly dummies

Y_t is trend variable

ϵ_t is error term

<u>Autoregressive model</u>

A weakness of simple naïve expectations model is that, the biological nature of agricultural production creates lags in production response, and price. In addition, the impact of changes in a supply or demand variable are not immediately reflected in price due to inventories and processing lags. These potential impacts on price determination processes might be useful in predicating future price changes. The naive model only utilizes the price from the immediately prior period to predict future price.

An alternative to simple naïve model is an autoregressive or distributed-lag model. This model is a form of regression model, but instead of the variable to be forecasted, being related to other explanatory variables, it is related to past values of itself at varying time

lags. A simple regression model can be used to predict future prices based on current prices. This model is called an autoregressive model and simply uses past prices as the explanatory variables. The term auto regression indicates that it is a regression of the variable against itself. Whereas the multiple regression model forecasts the variable of interest using a linear combination of predictors. The autoregressive model includes past prices as explanatory variables:

$$P_{t=}\alpha + \beta_I \sum_{i=1}^{n} P_{t-1+\epsilon} \quad (4)$$

Where as P_t is series under investigation, n is the order (length) of filter, α and β are coefficients, ϵ is error term.

In this model, seasonal lags are determined by knowledge of underlying prices. To forecast the monthly corn, soybean and wheat prices the below mentioned autoregressive model with three lagged variables were used.

$$Predicted\ C_{t=}\theta_0 + \theta_1 C_{t-1} + \theta_2 C_{t-2} + \theta_3 C_{t-3} \quad (5)$$

$$Predicted\ S_{t=}\sigma_0 + \sigma_1 S_{t-1} + \sigma_2 S_{t-2} + \sigma_3 S_{t-3} \quad (6)$$

$$Predicted\ W_{t=}\mu_0 + \mu_1 W_{t-1} + \mu_2 W_{t-2} + \mu_3 W_{t-3} \quad (7)$$

WhereC_t,S_t, W_t are the current monthly price for corn, soybean and wheat prices respectively

P_{t-1} is one month prior to time

P_{t-2} is two months prior to time

P_{t-3} is three months prior to time

Monthly Price Index

Developing a price index helps in identification of seasonal price patterns, which in turn help producers and businesses to make better buying, selling, and storage decisions. In this study, we calculated each month's price index for corn, soybeans and wheat, which gives the average price in that month as a percentage of the year's average price. Monthly price index for commodities can be calculated by taking the average of determined price for each month of the year, then calculating the overall average of all the determined prices in the data and lastly dividing each month's average price by the overall average price to obtain the monthly price index.

Relationship between exchange rate and commodity price

Relationship between exchange rate and corn, soybean and wheat prices are analyzed by using the simple regression model.

$$Y_{c=}a + bX_c + \in \quad (8)$$

$$Y_{s=}a + bX_S + \in \quad (9)$$

$$Y_{w=}a + bX_w + \in \quad (10)$$

WhereY_c, Y_s,Y_w are monthly corn, soybean and wheat prices respectively

a is intercept

b is slope

X_c, X_S, X_w are real monthly commodity exchange rates for corn, soybean, and wheat respectively.

$\in$ is error term

The monthly corn, soybeans and wheat prices, when seasonality, year, exchange rate are taken into consideration cane be predicted by using multiple regression model.

$$Y_{c=}\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\in \quad (11)$$

$$Y_{s=}\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\in \quad (12)$$

$$Y_{w=}\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\in \quad (13)$$

WhereY_c, Y_s,Y_w are monthly corn, soybean and wheat prices respectively

β_0 is slope

β_1, β_2, β_3, are slope for the independent variables

X_1 is seasonal dummy variables

X_2 is year

X_3 is exchange rate

$\in$ is error term

CHAPTER IV

RESULTS AND DISCUSSION

Table 1: Descriptive statistics of corn, soybean, and wheat monthly prices

Descriptive Measure	Corn	Soybean	Wheat
Mean	3.108	7.534	4.375
Standard deviation	1.479	2.995	1.784
Minimum	1.520	4.090	2.220
Maximum	7.630	16.200	10.600
T-value	34.90	41.78	40.74
P-value	<0.0001	<0.0001	<0.0001
Skewness	1.437	1.111	1.145
Kurtosis	0.992	0.089	0.402

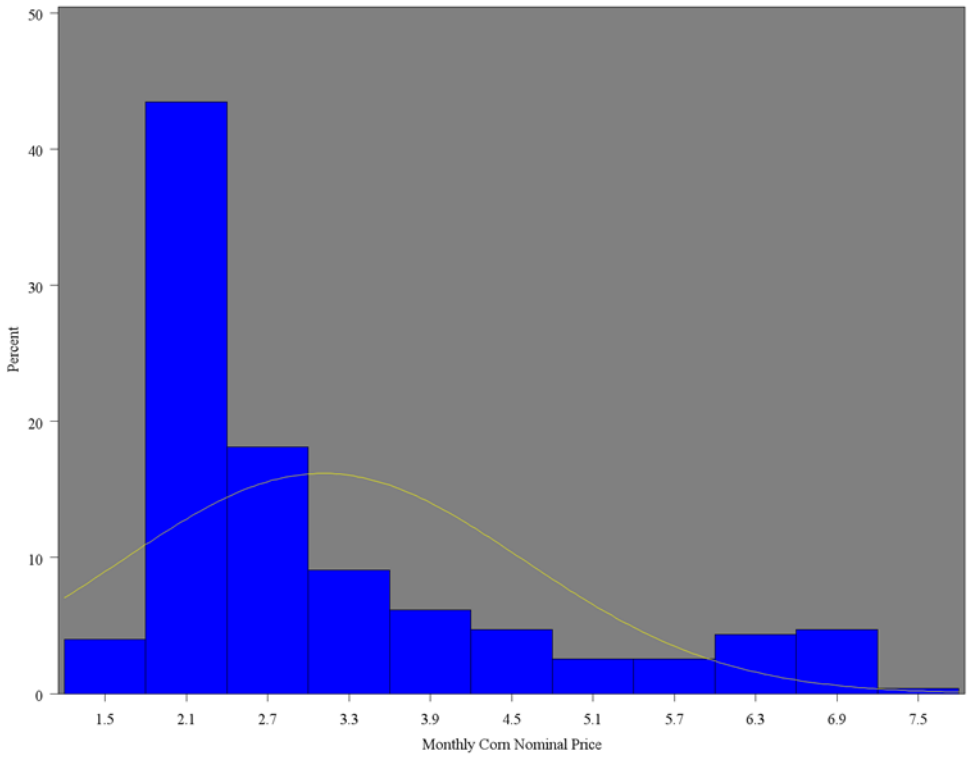

Figure 4: Histogram of monthly corn nominal price

Table 1, shows descriptive measures, specifically includes mean, standard deviation, minimum, maximum, t-value, p-value, skewness and kurtosis for the three agricultural commodities studied in this research. The mean monthly corn price for the data from 1991 to 2013 is $3.108, while the standard deviation is $1.479. Corn prices range from $1.520 to $7.630 between 22 years (Table 1). Positive skewness (1.437) in Table 1 is further supported by the shape of histogram (Figure 4). The mean of monthly soybeans prices for the study period is $7.534, and the standard deviation is $2.995. The soybeans prices range between $4.090 to $16.200 and exhibit positive skewness (1.111). The results in Table1 is further supported by the shape of histogram (Figure 5). Mean monthly wheat price is $4.375 for the 23 years of data and the standard deviation is $1.784. Wheat prices range between $2.220 to $10.600 and the positive skewness 1.145 in Table1 is further supported by the shape of histogram (Figure 6).

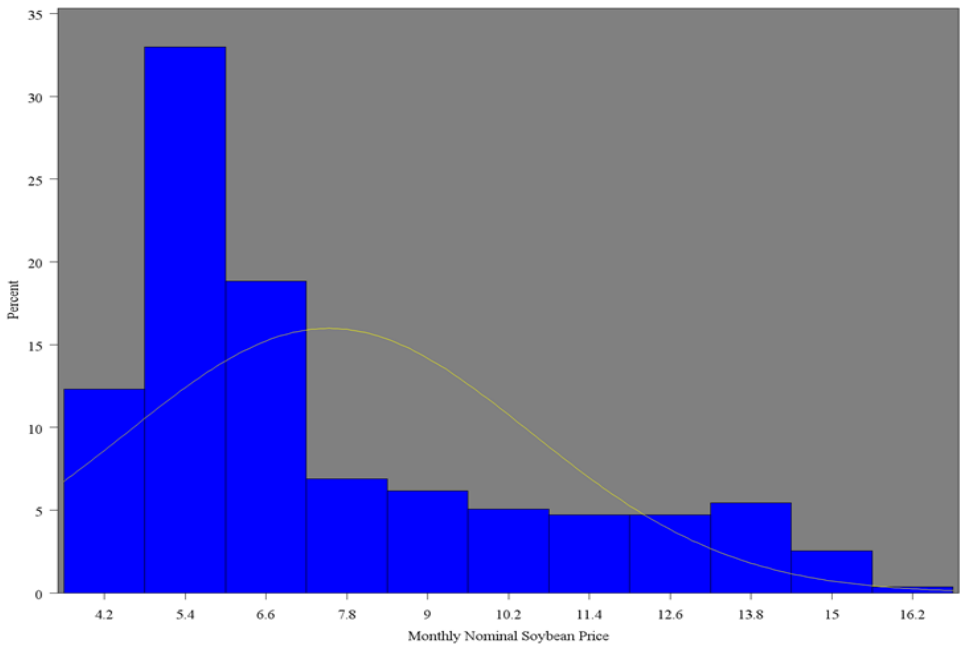

Figure 5: Histogram of monthly nominal soybean price

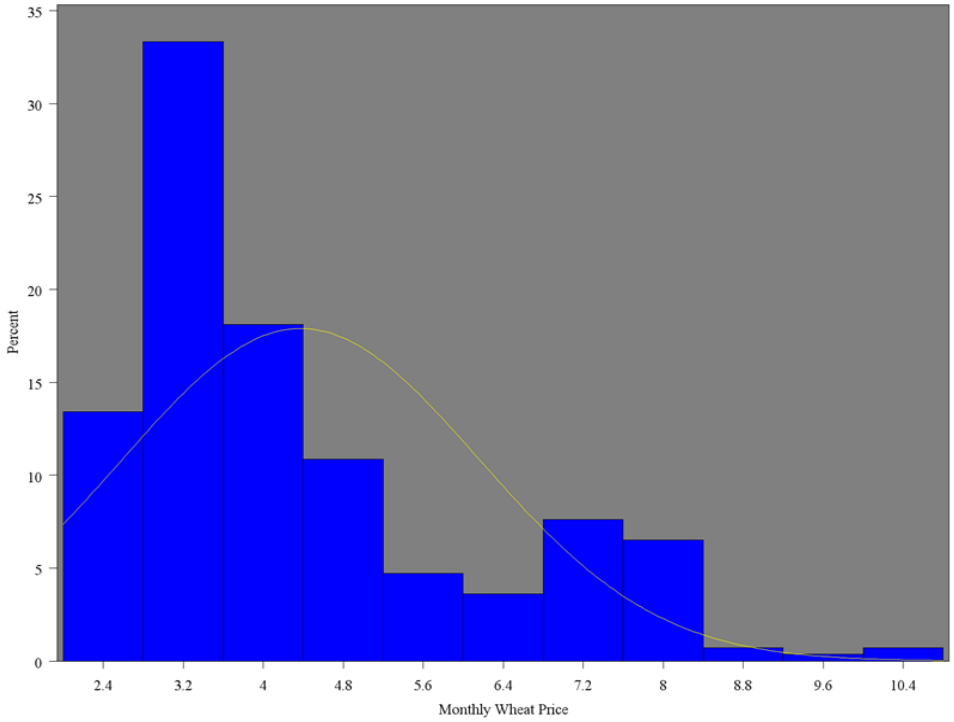

Figure 6: Histogram of monthly nominal wheat price

Table 2: Pearson correlation coefficients for monthly commodity prices

Pearson correlation coefficients			
	Corn price	Soybean price	Wheat price
Corn price	1.000	0.953	0.908
Soybean price	0.953	1.000	0.896
Wheat price	0.908	0.896	1.000

Table 2 includes the correlation coefficient which is the measure of linear relationship between paired commodities monthly prices. As the coefficient value of 0.953, 0.908 and 0.896 in the Table 2 indicates there is strong relationship between corn-soybeans prices and corn-wheat prices and soybean-wheat prices respectively.

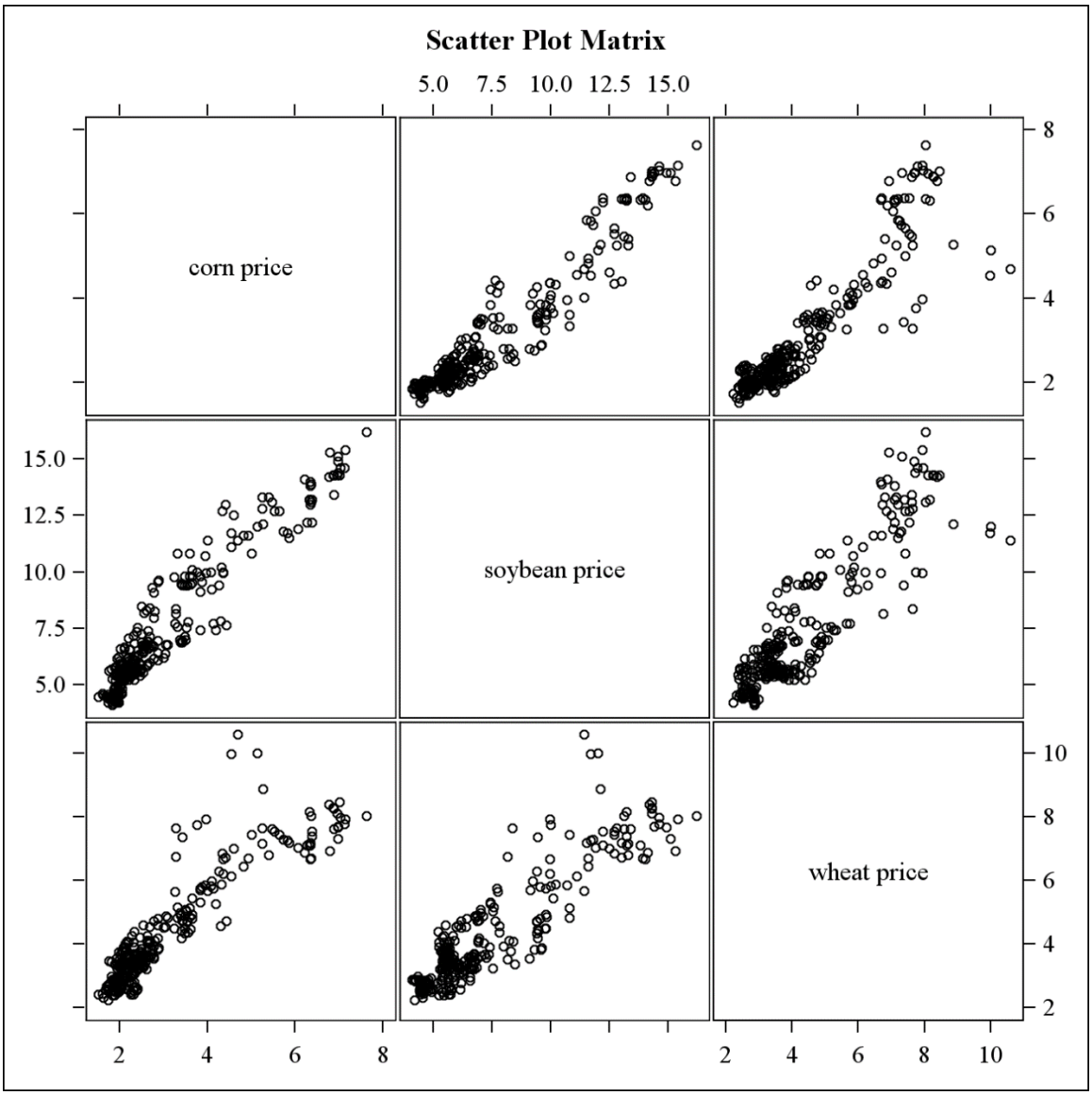

Figure 6: Scatter plot matrix of monthly commodity prices

The scatter plot suggests a definite relationship amongst the commodity prices. The Figure 7 indicates there is a strong positive relationship among corn, soybeans and wheat prices and we also note that there appears to be a linear relationship between the commodities.

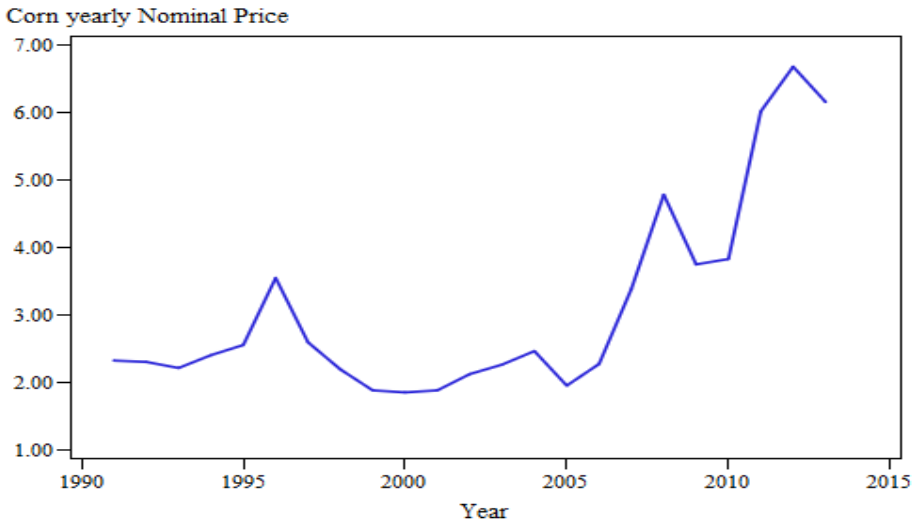

Figure 8: Line plot of corn average yearly nominal price

Figure 8 shows the average annual price for the 23 year study period. In the year 1996, the price of corn slightly increased and exhibited a decline immediately afterwards. Beginning in 2005, there is a sudden spike in corn prices due to ethanol demand and they further increased in 2012 because of the drought.

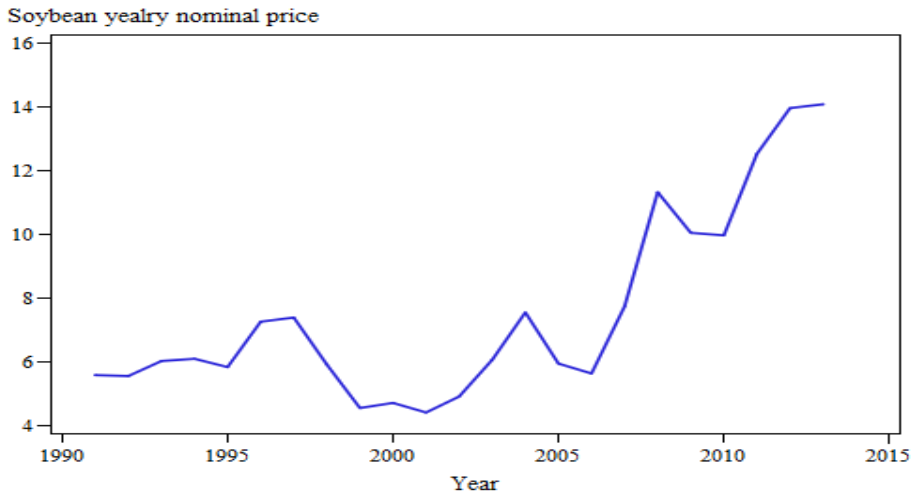

Figure 9: Line plot of soybean average yearly nominal price

As seen from Figure 9, soybeans prices show steady increase from 2000 to till date, because of huge export demand from china.

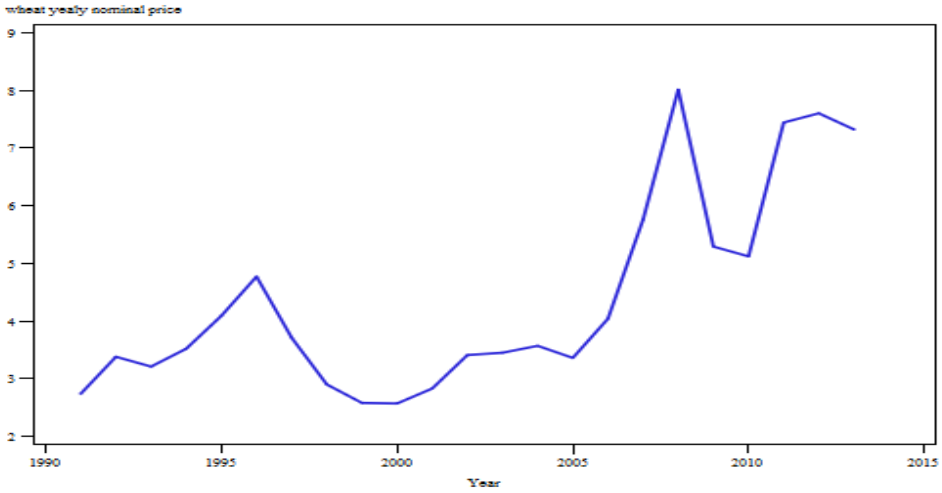

Figure 10: Line plot of wheat average yearly nominal price

Figure 10 shows that wheat prices decreased from 1995 to 2000, then an increased and a sudden decrease in price from 2008 to 2010 and a sudden spike in prices since 2011.

Regression analysis

Table 3: Regression results indicating the impact of calendar months

Month	**Corn**	**Soybean**	**Wheat**
January	0.001 (0.326)	-0.179 (0.616)	-0.143 0.380
February	0.076 (0.326)	-0.045 (0.616)	-0.056 0.380
March	0.118 (0.326)	0.061 (0.616)	-0.016 0.380
April	0.172 (0.326)	0.210 (0.616)	-0.041 0.380
May	0.193 (0.326)	0.371 (0.616)	-0.090 0.380
June	0.184 (0.326)	0.441 (0.616)	-0.324 0.380
July	0.138 (0.326)	0.445 (0.616)	-0.410 0.380
August	0.116 (0.326)	0.289 (0.616)	-0.241 0.380
September	-0.008 (0.326)	-0.097 (0.616)	-0.102 0.380
October	-0.089 (0.326)	-0.272 (0.616)	-0.002 0.380
November	-0.063 (0.326)	-0.094 (0.616)	0.030 0.380
Time	0.151* (0.010)	0.327* (0.018)	0.188* 0.011
Intercept	1.223*	3.512*	2.231*

*Denotes significance at 5% level, numbers in parenthesis indicate corresponding standard errors

Table 3 shows the impact of calendar months and year effect on commodity prices. The results show that the regression coefficient are positive for January through August and negative for September, October and November for corn. The intercept for corn is 1.223, soybeans is 3.512 and for wheat is 2.231. The regression coefficient for corn in January is

0.001, which is higher than in December, whereas the coefficient for November is -0.063, indicating that prices are -0.063 lower in November than in December. Results from the Table 3, show that none of the months had a significant impact on commodity prices, as all coefficients in the table are insignificant at 5% level. The negative regression coefficient for the month of January, February, September, October and November indicates that soybean prices are lower in these periods compared to December. Higher positive coefficient in June, July indicates that soybeans prices are typically high for these two months. The results for soybeans also shows that, for January to December, none of the coefficients are significant at 5% level. The results for wheat show that most of the calendar months had a negative coefficient indicating lower commodity prices than in December. November is the only month which has a positive coefficient. The results indicate that for January to December, none of the coefficients are significant at 5% level.

Autoregressive model

Corn, soybeans and wheat monthly prices are forecasted using an autoregressive model.

Predicted corn price with three lags can be represented in the following equation and the results are shown in Table 3

$$P_{t=} \propto +\beta_1 P_{t-1} + \beta_2 P_{t-2} + \beta_3 P_{t-3} + \varepsilon$$

Table 4: Autoregressive estimates for corn prices (3 lags)

Lag	Coefficient	t-value	p-value
P_{t-1}	1.321*	21.834	0.006
P_{t-2}	-0.261*	-2.630	0.009
P_{t-3}	-0.073	-1.212	0.226

As can be seen, the coefficients $P_{t-1,}$ P_{t-2} on the lagged prices are statistically significant, because t-value is greater than 2, and P-value is less than 0.05 respectively. The results further suggest that previous lagged prices are affecting current corn prices. P_{t-3} coefficient on lagged prices is not statistically significant. The R^2 value of 0.98 suggests that about 98% of the variation in current price is explained by past prices. The magnitude of the coefficients (in absolute value) decline with successively longer lags. These results suggest that the immediate past price has the largest impact on current price, with a declining effect as one moves backwards in time.

Table 5: Autoregressive model estimates for soybean prices (3 lags)

Lag	Coefficient	t-value	p-value
P_{t-1}	1.322*	21.803	0.001
P_{t-2}	-0.343*	-3.491	0.000
P_{t-3}	0.011	0.187	0.851

The results in Table 5 show that the coefficient for P_{t-1} and P_{t-2} are statistically significant, indicating that these two lagged prices are influencing the current soybeans prices. But the P_{t-3} is not statistically significant as their t-value is not greater than 2 and p-value is not less than 0.05. The R^2 value is 0.98, suggesting that 98% of variation in

current price is explained by past prices. The results suggest that immediate past price has the most impact compared to older prices.

Table 6: Autoregressive model estimates for wheat prices (3 lags)

Lag	**Coefficient**	**t-value**	**p-value**
P_{t-1}	1.452*	24.236	0.007
P_{t-2}	-0.620*	-6.2260	0.009
P_{t-3}	0.152	2.540	0.011

The results in Table 6 show that coefficient for P_{t-1} and P_{t-2} are statistically significant, indicating that these two lagged prices are influencing the current price. From the table, it is evident that the coefficient for the third lag is insignificant, indicating no impact on current price. The R^2 value is 0.97, suggesting that 97% of variation in current price is explained by past prices. The results suggest that immediate past price has greater impact on wheat compared to older prices.

Monthly price index

Table 7: Monthly price index for the agricultural commodities

Month	Corn		Soybean		Wheat	
	Monthly Average	**Monthly price index**	**Monthly Average**	**Monthly price index**	**Monthly Average**	**Monthly price index**
January	3.030	97.516	7.245	96.156	4.340	99.178
February	3.112	100.132	7.394	98.135	4.435	101.354
March	3.154	101.503	7.501	99.554	4.475	102.268
April	3.208	103.238	7.650	101.528	4.450	101.692
May	3.229	103.909	7.810	103.657	4.401	100.589
June	3.220	103.630	7.881	104.598	4.167	95.234
July	3.174	102.133	7.885	104.649	4.081	93.266
August	3.152	97.964	7.729	102.572	4.250	97.131
September	3.044	97.964	7.342	97.442	4.389	100.311
October	2.946	94.803	7.167	95.111	4.489	102.596
November	2.972	95.628	7.345	97.483	4.522	103.351
December	3.049	98.104	7.468	99.110	4.508	103.023
Overall average price	**3.108**	**100.00**	**7.535**	**100.00**	**4.375**	**100.00**

Table 7 shows that the monthly price index for corn is lower in October (94.803), while it is higher in May (103.909), and the overall average price during study period is $3.108. The soybeans monthly price index is lower in October (95.111), higher in July (104.649) and the overall average price for 23 years of monthly data is $7.535. The monthly price for wheat is lower in July (93.266), higher in December (103.023) and the overall average price for the study period is $4.375. These results indicate that as commodities exhibite seasonality, by having lower price during harvest and higher price during the planting season.

Relationship between exchange rate and commodity prices

Table 8: Regression results indicating the impact of exchange rate on corn monthly price

Variable	**Coefficient**	**t-value**	**p-value**
Intercept	8.101*	6.164	0.0002
Exchange rate	-0.048*	-3.807	0.0001

The t-value for the exchange rate coefficient is -3.807 indicating that it has greater influence on the monthly corn prices. The exchange rate coefficient is negative and significant, implying that the exchange rate has a negative impact on corn prices.

Table 9: Regression results indicating the impact of exchange rate on soybean monthly price

Variable	**Coefficient**	**t-value**	**p-value**
Intercept	21.624*	10.763	0.0002
Exchange rate	-0.134*	-7.037	0.0001

From the t-value and p-value in Table 9 which are greater than 2 and lees than 0.05 respectively, we can infer that exchange rate has a significant effect on soybeans monthly prices.

Table 10: Results for relationship between exchange rate and wheat price

Variable	**Coefficient**	**t-value**	**p-value**
Intercept	12.888*	11.934	0.002
Exchange rate	-0.080*	-7.914	0.001

Table 10 indicates that the t-value and p-value for exchange rate and intercept are greater than 2 and less than 0.005 respectively. This indicates that exchange rate has a significant effect on wheat monthly prices. Exchange rate proved to have a negative impact on corn, soybeans and wheat prices. The exchange rate has an effect on the trade surplus or deficit. In general, a weak domestic currency stimulates exports and makes imports more expensive. Conversely, a strong domestic currency hampers exports and makes imports cheaper.

Table 11: Regression results for corn, soybeans and wheat

Month	**Corn**	**Soybean**	**Wheat**
January	0.060 (0.247)	-0.080 (0.430)	-0.044 (0.265)
February	0.176 (0.247)	0.085 (0.430)	0.054 (0.265)
March	0.256 (0.248)	0.274 (0.430)	0.150 (0.265)
April	0.268 (0.247)	0.328 (0.430)	0.071 (0.265)
May	0.256 (0.247)	0.488 (0.430)	0.006 (0.265)
June	0.295 (0.247)	0.662 (0.430)	-0.229 (0.265)
July	0.212 (0.247)	0.593 (0.430)	-0.348 (0.265)
August	0.167 (0.247)	0.391 (0.430)	-0.173 (0.265)
September	0.054 (0.247)	0.040 (0.430)	-0.022 (0.265)
October	-0.071 (0.247)	-0.206 (0.430)	0.056 (0.265)
November	-0.054 (0.247)	-0.037 (0.430)	0.066 (0.265)
Year	0.187* (0.008)	0.355* (0.013)	0.202 (0.008)
Exchange rate	-0.109* (0.008)	-0.169* (0.010)	-0.095* (0.005)

*Denotes significance at 5% level, numbers in parenthesis indicate corresponding standard errors

When seasonality, year, and exchange rates are taken into consideration for predicting monthly corn, soybeans and wheat prices, the results indicates that year and exchange rates show significant relationship. From this we can infer that year and exchange rate have more influence on corn, soybean and wheat prices than monthly seasonality.

Forecasting

Table 12: Forecasted commodity prices using regression model with seasonal dummies

Month	**Corn**	**Soybean**	**Wheat**
January	4.821	11.179	6.407
February	4.896	11.318	6.494
March	4.938	11.418	6.534
April	4.992	11.568	6.509
May	5.013	11.729	6.460
June	5.004	11.799	6.226
July	4.958	11.803	6.140
August	4.936	11.647	6.309
September	4.828	11.268	6.448
October	4.740	11.085	6.548
November	4.760	11.268	6.580
December	4.820	11.378	6.550

To forecast corn, soybeans and wheat monthly prices, the regression analysis variable for each month is equal to one and yearly time trend equals to 2013-1990=23, and all other variables are zero. Notice that the dummy variable for each month illustrates discount for selling corn for that month, but for December we excluded the dummy variable.

Table 12 shows forecasted corn price for 2014 in the range of $4.74 to $5.013. From this we can infer that the price of corn is higher in May at $5.013, and lower in the month of

October at about $4.74. Figure 11 indicates that the price of corn started to increase from January-May and declined from June-October. Forecasted soybeans prices range from $11.085 to $11.803. Price of soybean is higher in July at $11.803 and lower in October at $11.085. Figure 12 shows that soybean prices start to increase from January to July and decline after October and wheat price range from $6.140 to $6.580. Prices of wheat are higher in November and lower in July. Figure 13 shows wheat prices start to decline from March and suddenly increase from July.

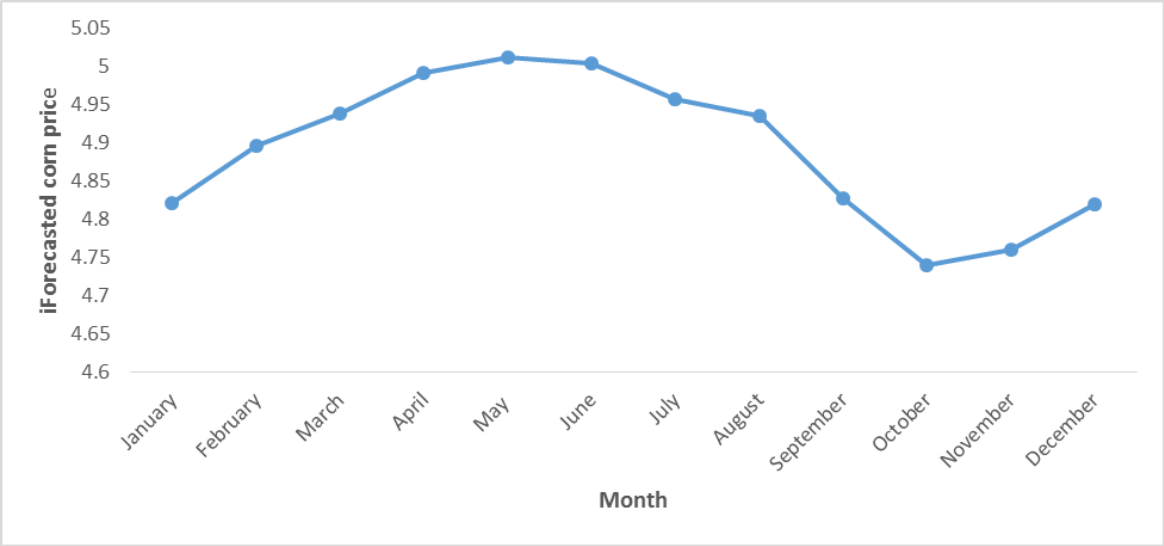

Figure 11: Forecasted Monthly corn price for the year 2014

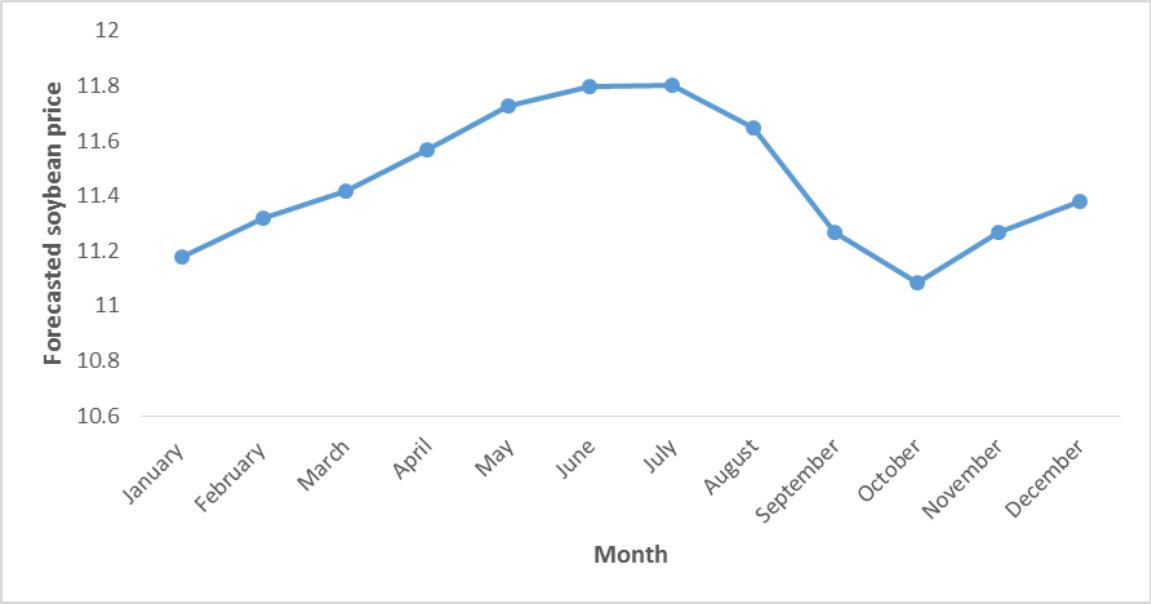

Figure 12: Forecasted Monthly Soybean price for the year 2014

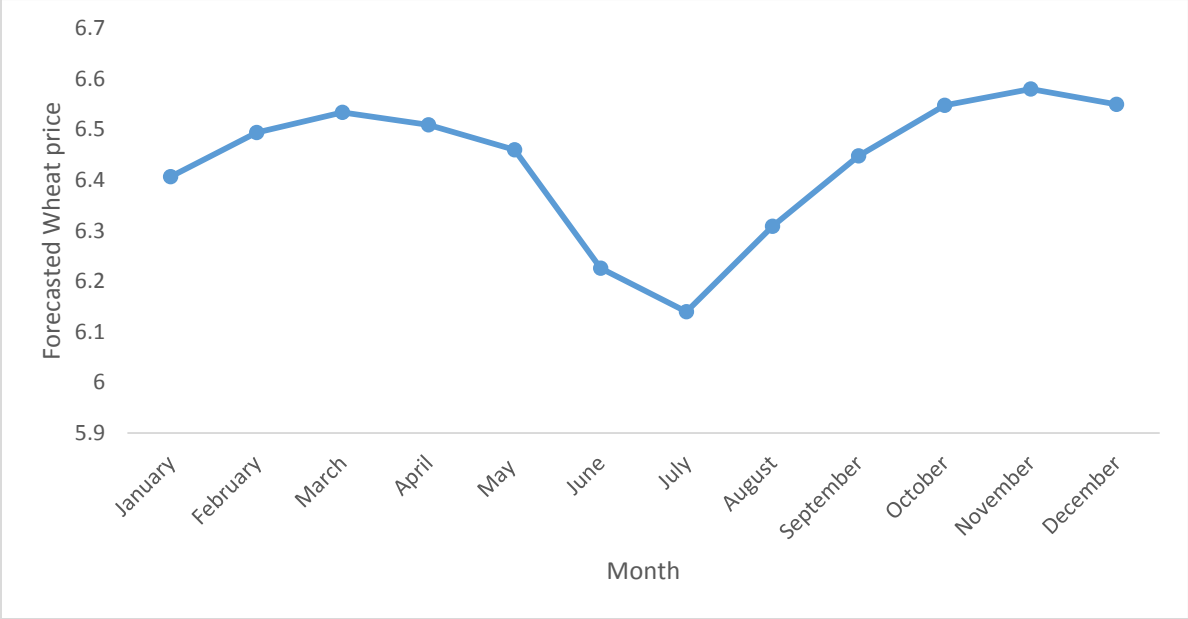

Figure 13: Forecasted Monthly Wheat price for the year 2014

Table 12: Forecasted commodity prices using autoregressive model for 2014

Month	**Corn**	**Soybean**	**Wheat**
January	2.261	5.724	2.432
February	2.302	5.743	2.460
March	2.341	5.769	2.490
April	2.379	5.788	2.445
May	2.416	5.816	2.441
June	2.453	5.851	2.467
July	2.489	5.884	2.500
August	2.525	5.916	2.532
September	2.560	5.947	2.561
October	2.594	5.977	2.589
November	2.628	6.007	2.616
December	2.662	6.037	2.642

Table 13: Akaike Information Criterion (AIC) for commodities

Commodity	**Akaike Information Criterion(AIC)**
Corn	-3.297
Soybean	-1.814
Wheat	-2.628

To forecast commodity prices, in this study, autoregressive models with three lagged variables were used, because the calculated Akaike Information Criterion (AIC) value is lower for all the three commodities (Table 13). Generally lower the AIC value, the greater the amount of information contained in the model. Table 12 shows that the forecasted prices for corn range from $2.261 to $2.662, soybeans prices range from $5.724 to $6.037 and wheat price range from $2.432 to $2.642.The forecasted results showed deviations when compared with actual price received for 2014.

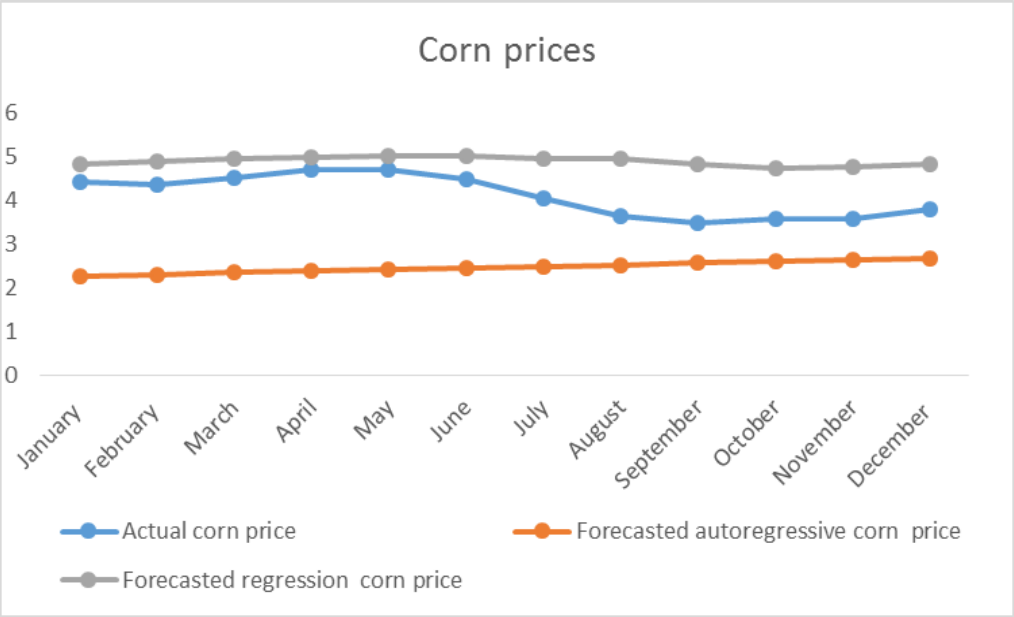

Figure 14: Forecasted Monthly Corn prices

Figure 14 shows the comparisons of actual monthly prices of corn for 2014 with forecasted monthly prices of corn using regression and autoregressive models. The results using regression model are on par with actual prices till July but after that it varied slightly. Whereas forecasted prices using autoregressive models are varied with actual prices received by farmers for 2014.

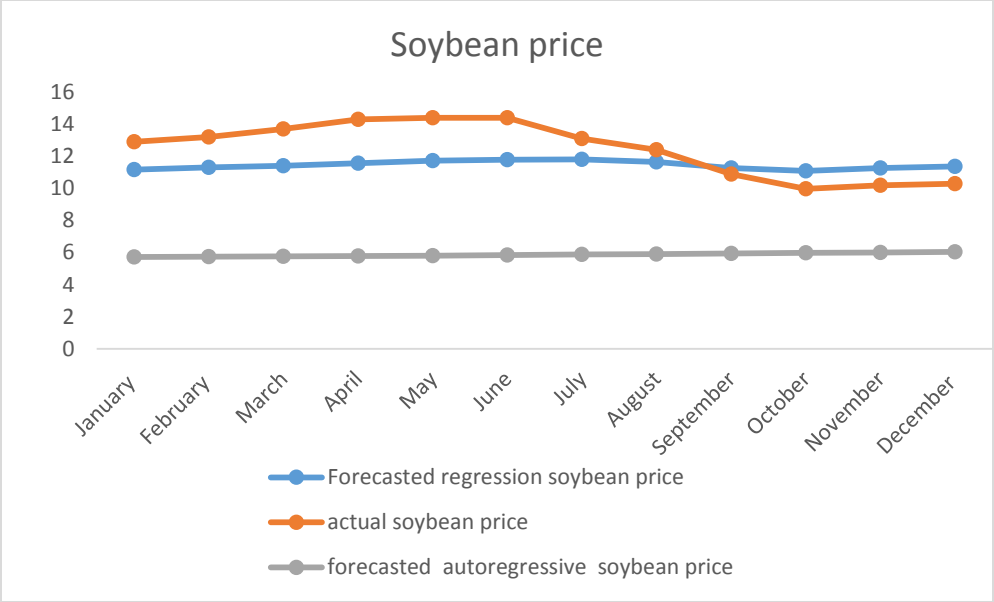

Figure 15: Forecasted Monthly Soybean prices

The above figure 15, indicates forecasted monthly soybeans prices using regression model are higher than actual prices till June and thereafter prices are more similar. But the forecasted prices with autoregressive models are varied with actual price received by the farmers for 2014.

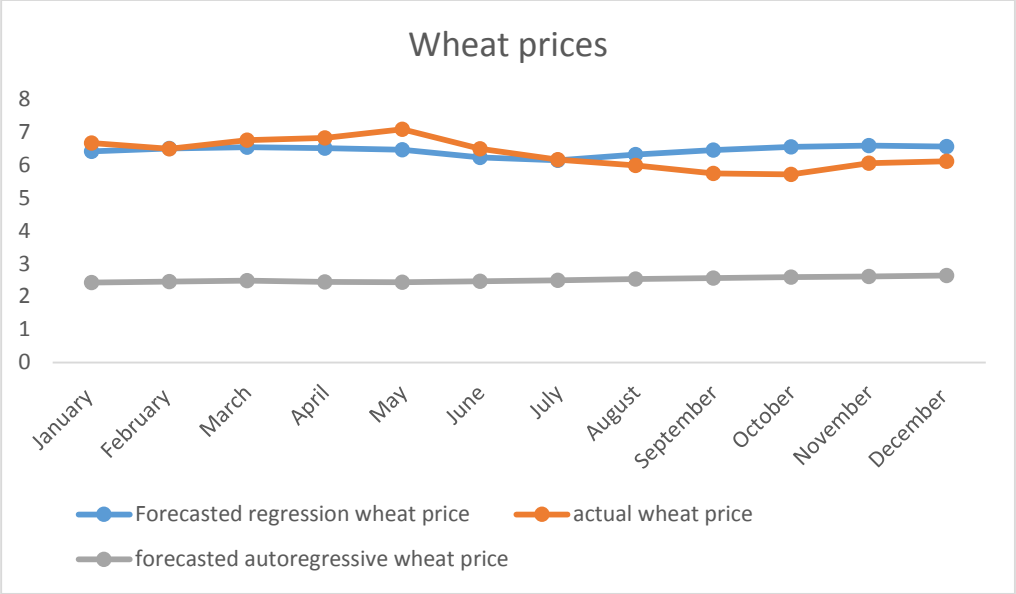

Figure 16: Forecasted Monthly Wheat prices

The forecasted results for wheat prices using regression model are similar to actual prices received by the farmers for 2014. Whereas forecasted results with autoregressive models are varied with the actual prices.

Table 14: Forecasted commodity prices using monthly price index

Month	**Corn**	**Soybean**	**Wheat**
January	7.216	13.990	7.835
February	7.209	14.033	8.007
March	7.206	14.236	7.976
April	7.123	14.518	7.932
May	4.883	10.884	6.840
June	4.974	11.244	6.571
July	4.902	11.249	6.621
August	4.800	11.641	6.799
September	4.702	12.180	7.021
October	4.526	11.817	6.950
November	4.303	11.844	7.234
December	4.316	12.388	7.108

Table 14 shows that the forecasted price for corn ranges from $4.303 to $7.216, soybean price ranges from $10.884 to $14.518 and the wheat price ranges from $6.571 to $8.007. Forecasted results are slightly varied with actual price for 2014.

CHAPTER V

SUMMARY AND CONCLUSIONS

The objective of the study was to forecast the monthly corn, soybean and wheat prices, understanding the relationship between the exchange rate and commodity prices and to analyze the effect of time, seasonality, exchange rate on the commodity prices. Time series regression model with seasonal dummies, autoregressive model and monthly price index were used in this study.

Forecasted results for the commodities using time series with seasonal dummies are on par with the actual prices received by farmers for the year 2014. The results from autoregressive model and the monthly price index are varied when compared to actual monthly prices for 2014. Exchange rates showed a negative impact on corn, soybeans and wheat prices. When seasonality, time, exchange rates are taken into consideration for predicting monthly commodity prices, the results shows that time and exchange rates have more influence on commodity prices than seasonality.

Suggestions for further study include forecast the monthly commodity prices using a real price. Real prices adjust to the changes in new technology, changes in consumer tastes and preferences, changes in government policies, world events, and so on. Modification to nominal price may give more accurate commodity forecast results. Another suggestion includes extending the study to forecast average yearly prices for commodity. It may help farmers to make a decision on continuing to grow the crop and also help them in increasing productivity of the crop.

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