KANSAS GRAIN SUPPLY RESPONSE TO ECONOMIC AND BIOPHYSICAL CHANGES

by

DAVID BOUSSIOS

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Major Professor
Andrew Barkley

Abstract

This research identifies and quantifies the impact of biophysical and economic variables on Kansas crop acreage and yields for the period 1977- 2007. Due to long production time requirements, agricultural producers must make vital decisions with imperfect information, based on expectations of future agronomic and economic conditions. This research analyzes the impact of price, climate, and yield expectations on crop acreage allocations and yield responses for the four major commodities produced in Kansas: corn, soybeans, wheat, and grain sorghum (milo). By modeling and analyzing both biophysical and economic variables, total supply response can be estimated for potential future changes in prices, yields, climate, and weather outcomes. The analysis of both biophysical and economic conditions allows for the estimation of supply response in the short and long run. The results provide updated, more precise results than previous research, which has often separated acreage and yield response.

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Chapter 1 - Introduction

Agricultural policies and market conditions have placed a growing importance on land use decisions. Historically, agriculture was focused solely on the production of food and fiber; the addition of biofuels has created a new source of demand for farm output. This demand shift has resulted in the conversion of many agricultural crops designated for energy use rather than food consumption. A large debate exists in the literature of the direct and indirect impacts of biofuels on land allocations and yields. Increasing yields through technological progress dampens the need for increased land intensification or expansion. While the full costs and benefits of biofuels are beyond the analysis of this research, estimating crop acreage allocation functions is a vital part of fully understanding the effects of biofuels and other changes in agricultural production and policies.

Understanding the supply of agricultural products is also important for analyzing commodity markets. The expansion and volatility of agricultural commodity markets have impacted all sectors of the economy. The recent volatility has many international policy makers considering major policy changes aimed at reducing the price variation. Wright (2011) suggested that some of the recent grain price volatility was due to "modest supply reductions." Explaining and predicting future supply shocks could reduce the amount of variation seen in the market.

Recent trends in climate and weather have resulted in the public's growing concern of the effects of weather and climate on our everyday lives. Climate is defined by the typical or "normal" temperature, wind, and precipitation of a selected region. Weather is characterized as the temporal changes in climate occurring daily. Knowledge of climate and weather is especially important in agriculture. Weather is a major determinant of an individual farmer's seasonal crop yields, while climate often plays a large role in the determination of which crops to plant over time. Short run crop allocation decisions may be impacted by unexpected weather patterns, while long run decisions are often affected by climatic changes and changes in the genetics of crops.

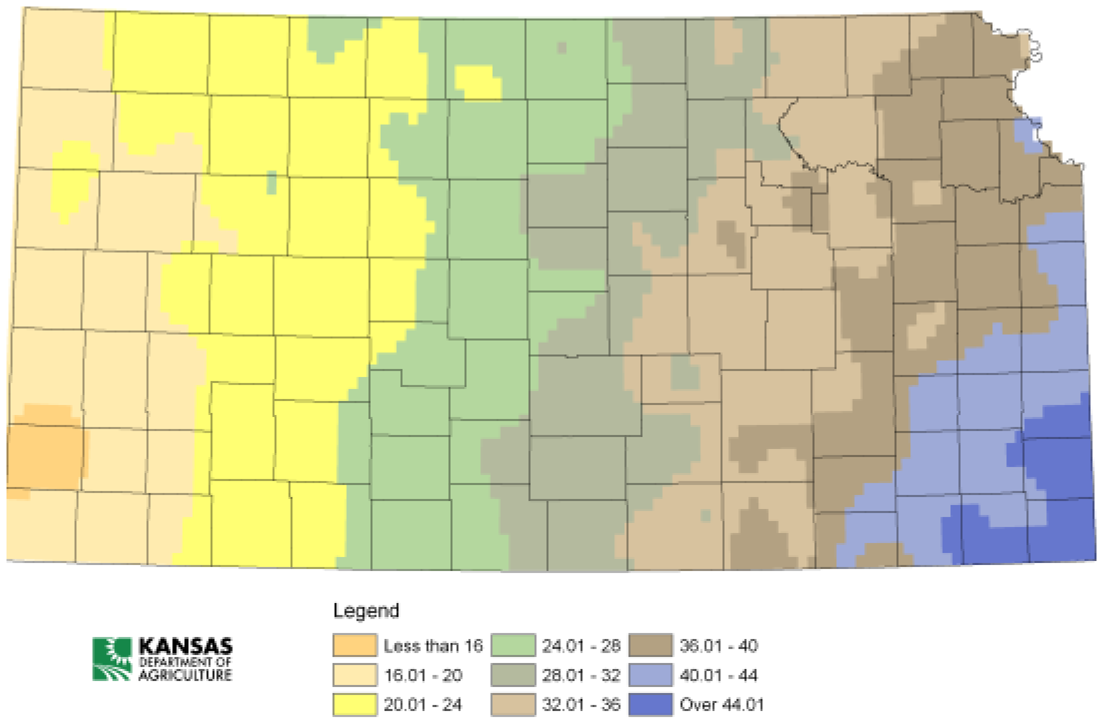
With the growing discussion and potential for long-term changes to weather and climates, estimating the potential effects of these changes will further provide insight into a situation that is unknown. While the prediction of such changes to climate and weather is left to other researchers, analyzing the impacts on agricultural commodity supply is important for a greater knowledge as agriculture and the world moves forward.

Research on the environmental impacts of production has tended to estimate the negative impacts due to the simplicity of soil erosion and nutrient measures. The influence of land use specifically on the environment has been researched by multiple sources and perspectives (Wu and Segerson 1995; Miller and Plantinga 1999). Evaluating the determinants of land use decisions can play an important role in environmental protection policies. Targeting the proper incentives will reduce the amount of unexpected outcomes.

The focus of this research is on the cropping decisions of Kansas farmers. As an agricultural state, Kansas is the number one producer of wheat and grain sorghum among all states in the United States. Additionally, it was ranked seventh among all states for combined sales of grains, oilseeds, dry beans, and dry peas in 2007. The total value of all agricultural products sold within the state is estimated at $14.4 billion in 2007, ranking fifth among states (USDA 2007).

This study presents a cross-sectional time series, or panel data analysis, at the county level for the time periods of 1975 to 2007. Figure 1.1 shows the annual normal precipitation for the 105 Kansas counties (Kansas Department of Agriculture 2009). Within Kansas, there is large variation in climate and acreage allocations across space.

Figure 1.1. Kansas Annual Normal Precipitation, 1971-2000



The western part of the state is characterized by drier climates with greater need for irrigation. The eastern half is a much wetter climate with large variance in rainfall. While many national or regional studies have studied the interaction of specific variables on supply responses, (e.g., Huang and Khanna 2010; Lubowski, Plantinga, and Stavins 2007; Yu and Babcock 2010; Morzuch, Weaver, and Helmberg 1980; Hardie and Parks 1997) the estimates presented here differ due to potential categorical differences across regions within the U.S. The cropping and production practices vary among regions due to weather, producer preferences, soil qualities, and prices. Kansas is a state agriculturally different from the Midwestern Corn Belt states and consequently the results are expected to differ significantly. Thus, there is a need to study supply response at the regional and state level.

The figures presented below are the county average yields for the four major crops in Kansas from 1975-2007 (U.S. Department of Agriculture, Data and Statistics n.d.).

Figure 1.2. Kansas County Average Corn Yields, 1975-2007

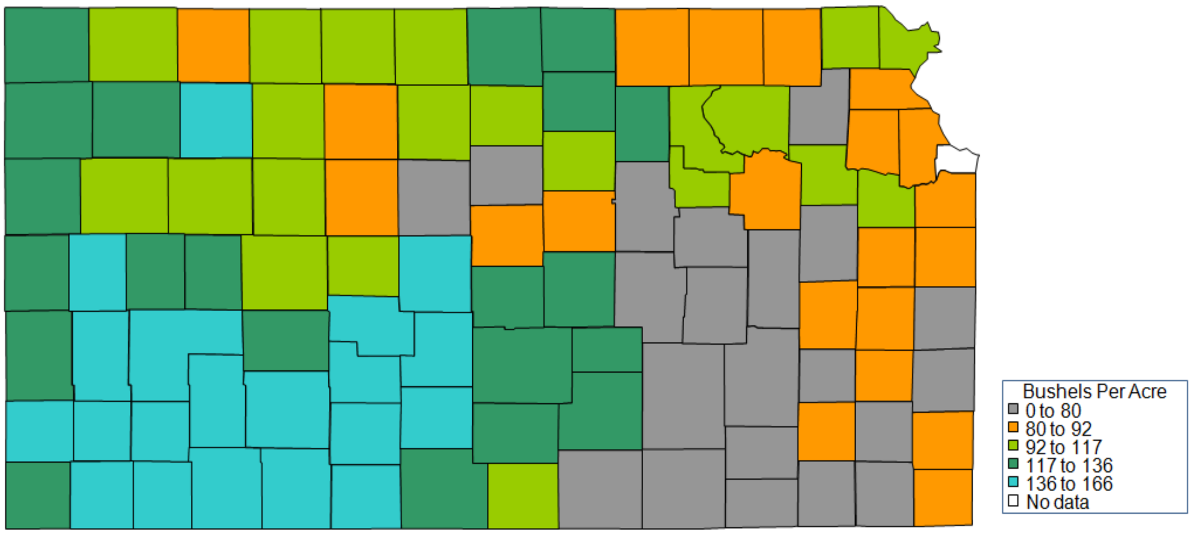


Figure 1.3. Kansas County Average Soybean Yields, 1975-2007

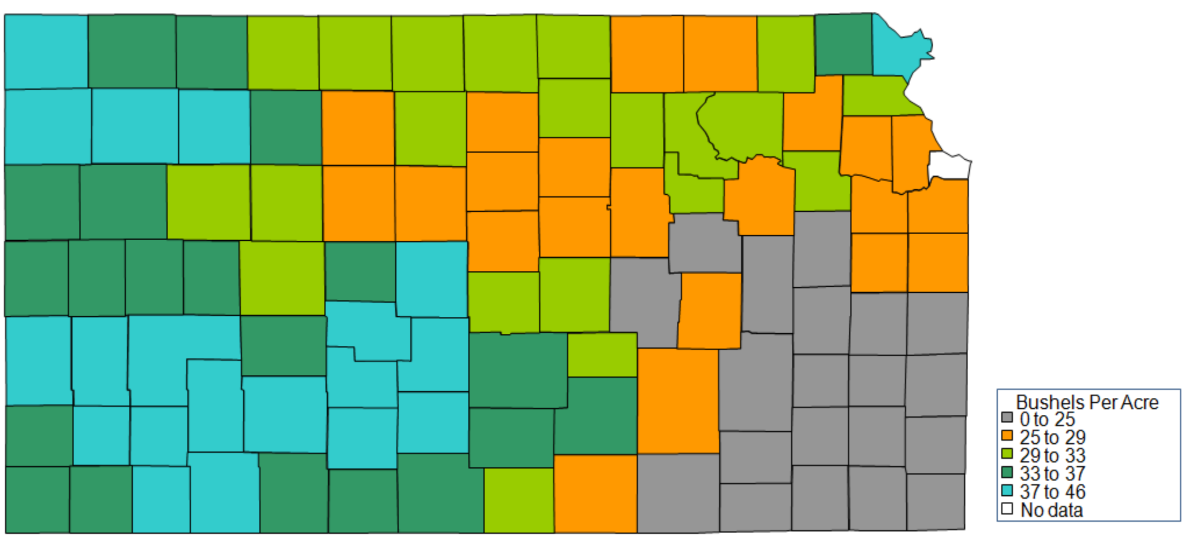


Figure 1.4. Kansas County Average Sorghum Yields, 1975-2007

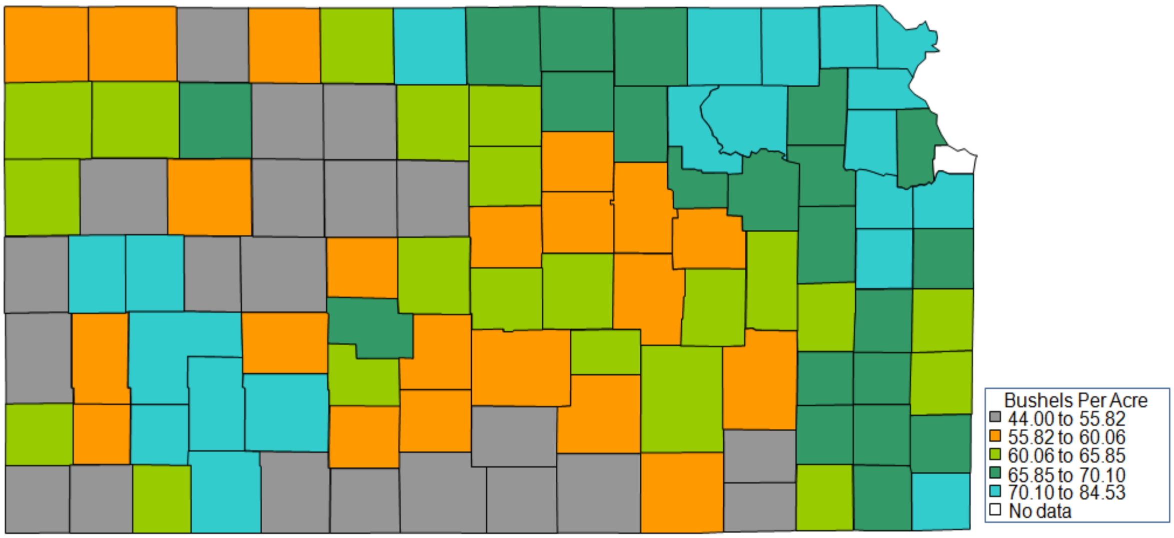
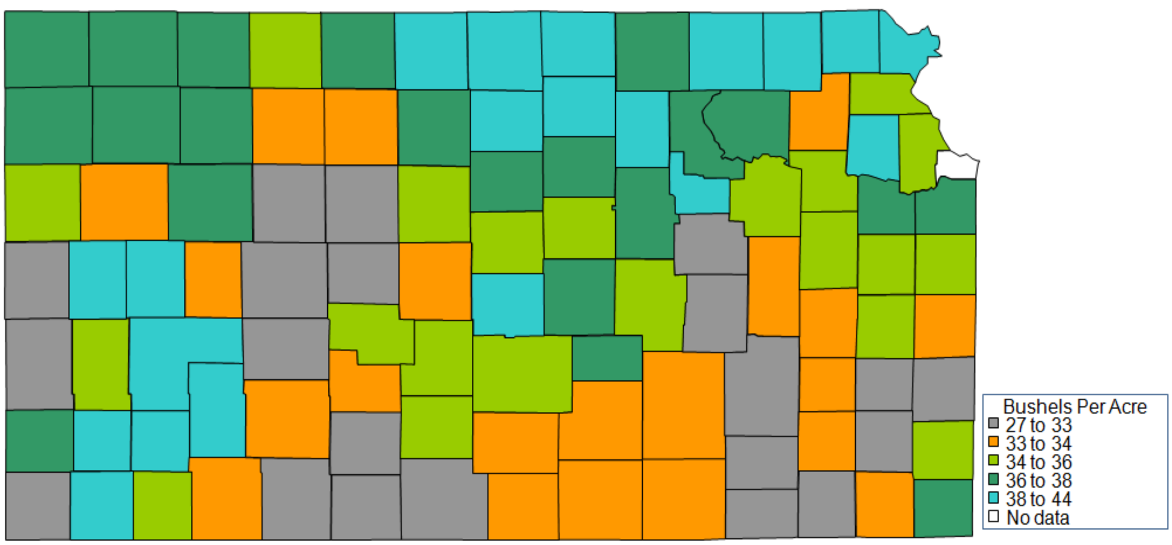


Figure 1.5. Kansas County Average Wheat Yields, 1975-2007



These figures show the distinct differences in yields for corn, soybeans, sorghum, and wheat across the state. The southwestern part of the state shows much higher average yields in corn and soybeans. This is due to the large number of farms using irrigation in those counties. Comparing the comparative advantages of counties when analyzing corn and soybean yields, it is clear there is a strong correlation. The explanation for this correlation is due to the substitutability and complementary relationship of the two crops. Sorghum yields tend to be higher in the northeastern part of the state due to higher precipitation levels. Sorghum is traditionally less likely to be irrigated then some of the other crops, thus as depicted in figure 1.4, yields are more likely to be impacted by precipitation levels. Wheat yields tend to be higher in the northern counties. Across the four crops three counties, Finney, Gray, and Haskell, are of particular interest. They have average yields in the highest twenty percent of counties, yet reside in a drier portion of the state. This contradiction to expected yields is due to the high level of irrigation and large scale commercial farming within those counties.

As shown in the figures above there are large variations within Kansas for expected yields. However, by restricting the sample to one state any categorical difference across states which influence yields is ignored. Every producer within the sample faces the same state level farm programs and local government. As past research has shown, the impacts of state and national governmental policies can dramatically affect producers' decisions (Wu and Segerson 1995; Morzuch, Weaver, and Helmberger 1980; Chembezi and Womack 1992). While accounting for these policy changes is important, mathematically quantifying the impacts is difficult. Confining the data to one state limits unnecessary or unquantifiable policy and program variations across space. This limitation increases the accuracy of the results for application to Kansas agriculture.

A goal of this research is to address the impact of weather and economic variables on crop yields. These findings provide insight into potential variations across crops and locations. The second goal of this study is to estimate acreage responses to varying price and yield expectations. Combining the results of acreage and yield will result in agricultural producers total supply response to prices and expectations. Many studies have neglected the impact of yield responses when estimating supply elasticities strictly through acreage decisions (Chavas and

Holt, 1990; Chembezi and Womack, 1992; Lin and Dismukes, 2007; Orazem and Miranowski, 1994). This research will advance the knowledge of the agricultural supply industry, which is important for informing policy makers, and the agribusiness industry. Understanding how prices and policy impact agricultural production decisions is important given the recent and potential changes in agricultural policies and climate.

The thesis follows the following outline. Chapter 2 presents relevant empirical yield and acreage allocation studies in a review of the literature. Chapter 3 builds the theoretical economic background for the study and derives important comparative statistics analyzed in this research. Chapter 4 describes the econometric models and data used. The results are presented and discussed in Chapter 5. The concluding chapter, Chapter 6, summarizes the findings and discusses potential implications of the results. The final sections of this thesis are the bibliography and appendices.

Chapter 2 - Literature Review

There have been a variety of empirical studies that have estimated and predicted land use decisions. The methods used for determining land use choices have varied greatly, depending on the parameters of interest and desired outcomes. While the models and techniques differ, the fundamental variables remain fairly consistent across analyses. This literature review is separated into subcategories within the land use field. Separating the variables into specific categories is important in understanding their varying impacts on land use. Lubowski, Plantinga, and Stavins (2007) stated, “land use decisions have depended critically on land quality and have been steered by anticipated economic returns.” The biophysical characteristics of land determine which economic opportunities are available to land owners. By integrating biophysical and economic variables, this analysis is able to greater quantifying differences across land through weather and climate, allowing the assumption of homogenous land types to hold.

Acreage Allocation

There has been a great deal of research on the topic of acreage allocation. Much of this research has focused on the impacts of prices, governmental policies, and risk. Seminal research on the supply of agricultural products was done by Nerlove (1956, 1979). He pointed out the importance of analyzing expected prices rather than lagged prices, when estimating land use and acreage decisions. He stated “Each past price represents only a very small short-run market phenomenon, an equilibrium of those forces present in the market at the time” (p. 499). Nerlove’s price expectations model was based on lagged acreage and prices.

Nerlove (1956) also discussed the concept of the “stationary state” in agriculture, which would conceptually imply the presence of no dramatic changes in production practices, techniques, or prices of inputs/outputs. In this model any supply/demand shock would only affect short run prices and outcomes. Subsequent short run acreage allocation would not fluctuate as expected prices would be more accurately measured by a long run average, thus lagged prices would efficiently measure producer expectations. As he stated, this relationship does not hold in actual practice because the markets are not stationary. The prices of inputs, role of technology, seed genetics, and a variety of other topics are changing continuously. This concept questions the use of lagged variables with non-stationary economies and prices. The lagged prices are a function of a variety of lagged supply and demand variables which provide that specific short run results. However, prices in subsequent years are a function of their specific short run demand and supply intersections. The only way in which lagged terms may impact present year prices is through commodity storage.

Morzuch, Weaver, and Helmberger (1980) created another way of forming price expectations to predict wheat acreage response to changing governmental programs and prices. By creating a ratio of the expected price of wheat to an index of the expected prices of other crops all through futures prices, they attempted to create a variable which incorporated substitution effects. With the substitutability of crops, they believed the comparative value of the crops was more appropriate. With comparative pricing, you measure the relative value rather than actual price. As crops are often substitutable, an increase in one price relative to another crops price would likely result in more acres planted. They found that the own-price elasticity of wheat to vary significantly by state and model, ranging from 0.13 to 1.50. States which produced spring wheat were shown to have higher elasticities in comparison to winter wheat elasticities. The estimated own-price elasticity for Kansas' wheat was in the middle range of their study at 0.41 or 0.32, depending on model selected. Their analysis also emphasized the impact of governmental programs affecting wheat acres' responsiveness to prices. The authors explained that in years with more government program payments, acreage was less responsive to prices indicating greater distortions of the market. Understanding the impact of governmental programs on farmers' decisions is thus important.

Bailey and Womack (1985) analyzed the differences in elasticities for wheat production throughout regions of the U.S. They found the southeastern and corn belt regions to have higher elasticities than the plain regions or the northwest. With these results, they proclaim regional characteristics are important determinants in acreage response functions. Government programs which do not account for these differences will inhibit the success of acreage programs.

Another study which estimated the differences in production through pooling of data was undertaken by Whittaker and Bancroft (1979). They analyzed corn production response in Indiana, Illinois, Ohio, and Iowa using lagged prices, binary state variables, and government diversion prices multiplied the fraction of acreage eligible acreage for diversion. Their results showed state dummy variables as the largest determinant of acreage responses. Price elasticities were estimated to vary between 0.22 and 0.26, depending on model.

Orazem and Miranowski (1994) investigated the impact of futures prices as well as expected future soil productivity on acreage decisions. Incorporating the expected future soil productivity allowed estimations to account for possible loss in soil quality over time due to farming. The relationship of cropping patterns and subsequent crop yields is a vital part of planting decisions. Crop rotation is an important aspect of acreage allocations. Their results confirmed that crop choices are determined by expected prices, as well as future soil quality. They also found that government programs limited the incentives for rotating crops for future increases in soil quality; "35% to 40% of the corn crop in Iowa is continuous crop" (p. 394). This showed that the incentives for continuously producing corn make up for yield loss due to degrading soil qualities. The subsequent lower soil quality could be augmented through fertilizer applications, according to the authors.

The impact of land quality and irrigation technology is a field of research that has been shown to significantly shape land use decisions. By creating a land quality index, Lichtenberg (1989) estimated the impact of land quality on acreage allocation. He investigated irrigated and non-irrigated corn, sorghum, wheat, soybeans, and small grains in western Nebraska. His results showed that land quality was a large factor in cropping decisions for all crops, with the exception of irrigated corn. This is due to the effect of irrigation technologies increasing marginal quality land. Lichtenberg (1989) found a strong relationship between irrigated corn and sorghum. As land quality increased, the need for irrigation declines leading to more acres of sorghum planted.

The relation of land quality and acreage allocation is further estimated by Hardie and Parks (1997). They used a multinomial logit model to approximate the impacts of revenues/costs, land quality indicators, and population descriptors on irrigated and non-irrigated farm land and forestry land. The higher quality land was more likely to be used as farmland, while the more marginal land is found to be allocated to forestry uses. Population density showed land was less likely to be enrolled in forestry or farming the denser the population. An important relationship between irrigated and non-irrigated farmland was the role of crop revenues and costs. An increase in crop revenue decreases the probability, while an increase in the costs of farming led to an increase in the probability of land being used for non-irrigated farming. This would explain why higher quality land is more likely to have irrigation systems.

The impacts of land quality on irrigation and crop choices are further shown by Green, et al. (1996) and Caswell and Zilberman (1986). By analyzing the impact of land quality on irrigation decisions, they showed that the biophysical needs for select crops shaped irrigation decisions. This relationship determinined the available cropping decisions for farmers. Agricultural producers analyze their land qualities and producable crops and further decide if augmenting their land quality with irrigation systems is economically profitable.

Moore and Negri (1992) examined the effects of water allocation on cropping decisions. By taking the perspective of a change in water allocation from the Bureau of Reclamation, they found "A simulated 10% reduction in water supply generates price changes ranging from 0.8% to 4.6% for three major crops (fruit, rice, vegetables)" (p. 39). This was due to changes in supply from farmers reallocating their land to different crops. With a lack of significance in own-price or cross-price variables for many crops they found weather and availability of water as more significant determinants of crop allocation than input or output prices. This could have been due to the full effects of water on cropping decisions. However they also noted by using lagged prices, their estimates may not have fully captured the individuals' perspective for crop allocation or expected future earnings.

The role of risk has been found to be an important factor in cropping decisions. Researchers have attempted to incorporate risk in a variety of ways. Chavas and Holt (1990) incorporated risk by looking at how producers' acreage allocation is effected by wealth, and the variances of yields, own, and cross prices. Looking specifically only at corn and soybeans, they found that soybeans were more elastic in comparisons of own-price and wealth elasticities; the corn own-price supply elasticity was estimated to be 0.158, while the soybean supply elasticities was 0.441. The explanation provided was that corn prices have historically been more governmentally supported. A higher variance in price for soybeans leads to more acres planted for corn as expected. However, higher variances in corn prices were shown to decrease acres planted for soybeans, which is not consistent with standard economic theory. This result would follow theory if the distribution of corn prices were skewed to the right, where any expected increase in variance was more likely to result in an increase in corn prices.

Lin and Dismukes (2007) estimated the impacts of risk and counter-cyclical payments on supply decisions. They estimated own price elasticities that were consistent with other studies; 0.170, 0.295, and 0.336 for corn, soybeans, and wheat respectively. The purpose of the study was to estimate the effects of risk on producers' decisions. Incorporating own price variance for each crop, they found that the impacts to be limited. Only the soybeans' own price variance variable was found to statistically significant. These limited impacts showed producers did not fully consider price risk as a deciding factor in cropping allocations.

Initial wealth significantly impacted the total number of acres planted. The overall wealth elasticity for all crops was 0.031. For individual crops the results vary significantly, 0.163, -0.051, and -0.201 for soybeans, corn, and wheat. These results indicated significant differences in crop allocations across individuals of varying wealth. The authors noted that the difference in signs could be due to governmental programs over the sample period. However, soil quality could also be important. Farmers with higher initial wealth may have been more willing to forego earnings in the short run by planting soybeans to increase soil quality, increasing the long run profitability of their farm. The effects of counter-cyclical payments were found to increase acreage of all crops by less than 1%. These payments provide limited impacts on short run planting decisions.

Whitson et. al. (1981) used a linear programming model to predict cropping decisions and capital purchases, with variable weather. By analyzing available production time as a function of expected weather patterns, the ability to plant or harvest crops within a specfic period of time depended on the crop planted and machinery available. Their results showed as confidence levels of farmers having enough time to complete tasks increased, farms switched planting practices away from cotton towards sorghum and further diversified their acreage. The diversification was seen to reduce capital investments. This research emphasized the importance of farmers' perception of local climate on cropping patterns and capital purchases.

Huang and Khanna (2010) estimated acreage response using two lagged acreage measures, crop prices, one year lagged input prices and weather variables, and various price and yield risk variables. The risk variables were defined identically to Chavas and Holt (1990), and the impact of these variables showed negligible effects. The fertilizer price index was positive across many of the crops, indicating possible other interactions present. The authors explain this finding by stating "higher fertilizer prices reduce the intensity of cultivation but leads to changes at the extensive margin and substitute land for fertilizer" (p.17). The weather impacts were found to be significant, although in actual size only limited effects on county acreage. Corn price was positive for the wheat models, contradicting the theoretical concept of crops being strict substitutes in production.

Acreage is just one part of agricultural supply functions. It determines many of the costs due to technology requirements and production practices, though profits are obtained through the physical product produced. Understanding how and why crop yields are impacted furthers the knowledge of producer behavior and the impact of uncontrollable factors on production.

Crop Yields

Crop yields are affected by a variety of economic and climatic factors. There has been extensive research from the agronomy profession trying to estimate the impact of weather on yields. Agronomic studies are often done through advanced weather metrics and field level data using homogenous production practices. This method provides great insight into the plants' growth and maturation process as it holds farming practices constant. Economists have researched how these weather and climate factors affect producer behavior. A review of the research on the impact of weather and economics on yields is presented below.

Climate and Weather

A variety of studies have estimated the impact of climate and weather on yields. Early research looked at the different approaches to measuring the impact of weather on crop yields by creating indices (Shaw 1964; Oury 1965). Limited to aggregate temperature and precipitation data, they created weather indices. By adding a weather index to a regression analysis, they maintained higher degrees of freedom and removed insignificant variables. Shaw, however, critiqued his own index by showing it indirectly incorporated the impacts of technological advances. A drought in later years may have shown a greater impact on yields than it would in recent years due to irrigation technology and seed genetics. This research showed the difficulty of econometrically separating agricultural progress from changes in weather patterns. The use of a trend variable is used to quantify the effects of categorical changes across time specifically technology.

Nelson and Dale (1978) further accounted for advances in technology and weather interaction by creating time trend variables. By adding linear and quadratic time variables, they attempted to separate the impacts of weather and technology. However, they showed that it is difficult to quantify technological increases through time variables. The data are often greatly impacted by how the trend variables are defined. The study used data for the time period of 1957 to 1975 and re-estimated their results to compare against the actual results from 1971-1975. They found that their yearly trend variable hid the impacts of weather variability on yields. With trend variables, the authors explained the variation across time, however as the authors noted the reasoning for selecting 1971-1975 was due to the limited progress in agricultural technology during that time period. However, their results show strong impacts of the time variable over this time period. With the limited expected technological increases during their time period of analysis, the impact of the variable was expected to be negligible. The time variable was likely masking the weather interactions.

Another important aspect of their study was how the authors incorporated weather, specifically how they condensed weather by specific growing seasons and departures from the normal mean. By limiting their weather variables to preseason precipitation and monthly growing season precipitation and temperature, they captured what they expected to be the most relevant weather for predicting corn yields. The weather was measured by the difference from the average across the time period of interest. This measurement is used based on the belief farmers take technology and climate as given, and apply their farming practices according to these expectations. Any variation in the monthly weather from the expected climate would be projected to impact yields.

A model which specifically incorporated the growing season weather variables was undertaken by Kaylen and Koroma (1991). Their model estimated corn yields with a stochastic trend term and monthly temperature and precipitation indices. The weather variables were normalized to a mean of zero, and an additional variable was the normalized variable squared to incorporate diminishing marginal returns for weather. Their results showed the average impact of weather on yields over the respective time period of analysis, 1895-1988, was four bushels per acre. A majority of the yield was captured through their trend variable. The aggregation of the weather limited the significance of much of their weather results.

Thompson (1975) took another approach by looking at the effects of climate and weather on grain production in the United States. By specifically analyzing the effects of weather variability on yields, Thompson calculated the impacts of a departure from normal weather patterns on yields. Looking at precipitation and temperatures, he found higher yields when precipitation was higher and temperatures were lower than the local averages. He stated “The highest yields in Kansas have been made with cooler than normal weather and greater than normal precipitation” (p. 188). Furthermore yields changed exponentially as the weather increasingly deviated from the norm. The impacts of the deviation of weather would show farmers selected their crops and took weather as given with only limited methods to adjust for variances, thus the larger impacts of weather playing a more significant role on yields.

A recent study measured the impacts of drought on corn and soybean yields over time. Yu and Babcock (2010) found both crops have become less susceptible to drought over time. They indicated a variety of reasons for the increased drought tolerance, including seed genetics and the consolidation of farms leading to fewer and more talented farm managers. These results further point to the need for trend variables to quantify the differences in farming practices and technology over time.

Schlenker, Hanemann, and Fisher (2004) provided another look at measuring growing conditions for farms east of the 100^{th} meridian. The reasoning behind analyzing only farmland east of the meridian is the relationship of precipitation to land quality and management techniques. This approach was taken because the effects of precipiation are significantly different for those areas which irrigate their farmland. By implying all acres East of the 100^{th} meridian do not irrigate they tried to capture the effects of precipiation across this nonirrigated land and thus hoped to create a more homogenous land sample.

To analyze the impact of weather, Schlenker, Hanemann, and Fisher (2004) moved away from a simple mean temperature measures toward a variable called degree days. Degree days was "defined as the sum of degrees above a lower baseline and below an upper threshold during the growing season" (p. 7). This was done under the belief there are certain ranges of temperatures in which crops grow best. Each additional degree within the threshold is expected to have a positive effect. A simple linear measure would not fully capture these temperature effects. Their results find degree days as a good estimator of farmland values which are theoretically correlated with expected crop yields and soil quality.

Recent studies by Schlenker and Roberts (2006, 2009) demonstrated the nonlineararity of the impact of temperature on yields. One study in particular looked at the optimal temperatures for corn, soybean, and cotton. The study found a positive quadratic relationship of temperature to yields with local maximum temperature to yields at 29°C, 30°C, and 32°C for corn, soybeans, and cotton, respectively. These results further show the nonlinear relationship of weather and temperature and the importance of incorporating a non-linear measure of weather variables.

Lobell and Asner (2003) estimated the impact of temperature, precipitation, and solar radiation on U.S. corn and soybean yields. The results found no significant impact of solar radiation and precipitation on yields. They found yields would decrease by 17% for every degree increase in growing season temperature. The lack of significance of solar radiation may be a result of the high correlation with temperature. Weather data have been shown with higher monthly temperatures less precipitation occurs, furthering the impact of the correlation of variables. These are possible explanations for why their results showed temperature as the sole significant determinant of weather on yields.

As the research has shown, yields are greatly impacted by weather. Combining the empirical research on yields and acreage response furthers the knowledge of total supply response to changes in weather and prices. Seperation of the two supply components limits fully understanding agricultural supply. Production practices are greatly dependent on farm expectations, which impact effect both acreage and yield decisions. The coupling of these response functions allows greater insight into potential supply shifts from policy changes or changing weather patterns.

Economic Considerations

The economic factors affecting crop yields are often characterized as producer yield response functions, defined as the response of a crop yield to a change in input or output prices. These prices often affect the application of fertilizers and management practices. Houck and Gallagher (1976) estimated U.S. corn yield response. To incorporate prices, the researchers included one variable defined as fertilizer price divided by output price. By combining input and output prices as a ratio, they forced a strict homogeneity of degree zero in prices. This implies that if both prices doubled, the rate of which fertilizer was applied would not change. The price ratio is used to further estimate how farmers are expected to adjust input levels as the ratio of input and output costs change. The authors found that corn yields were highly sensitive to prices, holding all else constant. Their research showed that by ignoring the producer's yield response to prices, acreage response measures would underestimate total supply response to a change in prices. Corn yield elasticities ranged from 0.24 to 0.76 for corn.

Choi and Helmberger (1993) estimated the yield responsiveness of corn, wheat, and soybeans. They estimated yield-output elasticities by independently calculating a fertilizer demand elasticity and the yield-fertilizer elasticity. The product of these elasticities are yield-output elasticities. The yield-output price elasticities were 0.27, 0.03, and 0.13 for corn, wheat, and soybeans, respectively. The higher elasticity for corn is consistent with typical cropping practices as corn requires more nutrients for production thus is more sensitive to fertilizer prices. They further stated the elasticities may be upward biased, especially corn, due to technological progress in seed genetics.

Another important finding of Choi and Helmberger (1993) was the impact of acres planted on yields. The authors noted, and theory would predict, that as output prices increased the number of planted acres of a crop would increase. Farmers would plant more acres with the higher priced crop, and theoretically these acres would be of lesser quality than the acres originally planted. As additional acres are planted on the extensive margin, this relationship would lower the measured aggregate yields of cropland. Their results, however, showed no effect of an increase in acres planted on measured yields. The results incorporated the impact of government farm programs which idle acreage. The effects of acreage and land idle programs are likely to impact the quality of land in production, thus effect yields. However their results are inconsistent with land quality theory.

Menz and Pardey (1983) presented two models. First, an analysis of U.S. corn yields through logged nitrogen application rates, July precipitation of large corn producing states, and a time trend. The results found the impact of their weather variable was limited but nitrogen applications rates to be significant determinants of yield. The three trend terms, linear, log, and square root were significant with neither term significantly better at predicting yields.

Their second model replicated Houck and Gallagher's (1976) results by adding the most recent nine years to the original model, including 1972-1980. Their results showed yields to be unresponsive to the original fertilizer-output price ratio over the new time period. These results are explained by a positive and insignificant price coefficient from the additional years, 1972-1980, thus questioning previous research and hypothesizing a categorical change in production behavior over this time period. The significant change in production practices was explained by the researchers by a decrease in fertilizer application rates per acre planted, as their results also showed. The application rate impacted the effect of the price ratio would have on yields.

McCarl, Villavicencio and Wu (2008) estimated the impact of aggregate crop yields. Through analyzing the impacts of yearly weather measures at the state level and regional dummy variables, they found that the most significant determinants of yield were the regional dummy variables and a precipitation intensity measure. The intensity measure is calculated by dividing the greatest month of precipitation over the yearly total. These results showed many biophysical impacts are unexplainable when data are highly aggregated.

While many of the studies listed earlier analyzed the economic/social impacts on yields, few have coupled this analysis with such in depth biophysical data as Kaufmann and Snell (1997). The biophysical data were analyzed through multiple temperature and precipitation measures over six phenological stages of corn growth. The terms included average daily minimum, mean, and maximum temperatures, as well as seasonal and daily precipitation measures. Many of the biophysical terms were in quadratic functional form. While the economic variables focused on farm level data; prices were analyzed as one variable equal to loan rates over lagged prices, and deflated by an input index. This pricing method resulted in the largest coefficient of their regression further supporting the validity of yield-output response research. Some of their important acreage impacts on yields show significant returns to scale among farms and negative impacts of marginal acres on yields.

Huang and Khanna (2010) estimated corn, wheat, and soybean yields for all counties within the United States. They attempted to incorporate weather using quadratic monthly precipitation measures, the monthly maximum temperature minus the minimum, and quadratic degree days. Prices were included through lagged prices and a USDA fertilizer index. They found that both input and output prices significant with the expected theoretical signs. Their results showed significance in many of their variables with the largest marginal coefficients for the variable measuring the proportion of acreage irrigated. The significance of their variables was likely due to the large number of observations in their models. They also estimated the impact of climate change through increased temperatures, showing decreasing yields for corn and soybeans and unclear results for wheat.

Summary of Literature Review

The literature is fairly consistent on the significant variables for estimating yield and acreage response models. A variety of weather variables such as solar radiation, and evapotranspiration, have been examined extensively in the agronomic community, however, the fundamentals of simple precipitation and temperature seem to be the most important. The simplicity of the two measures for climate and weather increase the degrees of freedom in statistical models and may capture the vital information of other measurements. The expected relationship between precipitation and temperature with more complex weather measurements may only obscure results due to the high intercorrelation among the variables. These variables may also be site and time specific and such data is not available for aggregate studies. Another important finding of the effect of weather is the non-linearity of weather variables. Earlier studies showed that incorporating quadratic weather variables improved statistical fit and demonstrated the varying marginal returns of weather.

As expected, acreage response studies have been heavily dominated by input and output prices. While the empirical results have shown the significant effect of prices, own-price elasticities have been inelastic. A table of historical estimates for own-price acreage elasticities of crops is in table 2.1. Risk has been found to impact cropping decisions as well, but the success of these results has been mixed. The lack of statistical significance or limited marginal effect of the risk variables, question the ability of these variables to efficiently and effectively quantify risk. Government policies have played a large role in cropping decisions. Much of the research has incorporated governmental programs with binary or integer variables. These variables, however, are more indicators than definite responses to policies. They were added as an attempt to measure policies, but may also quantify significant background noise due to such things as changes in producer preferences or technological progress over time, which are often unrelated to policy. Specifying institutional changes in non-stationary agricultural production has proven to be difficult or impossible econometrically, however incorporating such changes are important. Advancing the research on total supply responses will allow a greater understanding of markets resulting in more perfect information and less market volatility.

Table 2.1. Historical Own-Price Acreage Elasticity Results

Study	Crop and Model Used		Own-Price Acreage Elasticity
Bailey and Womack (1985)	Wheat	Southern Plains	0.246
		National	0.343
Chavas and Holt (1990)		Corn (Compensated)	0.158
		Soybean (Compensated)	0.441
Chembezi and Womack (1992)		Corn	0.156
		Wheat	0.108
Huang and Khanna (2010)		Corn	0.510
		Soybean	0.487
		Wheat	0.067
Hardie and Parks (1997)	Irrigated Farmland	Revenues	0.097
		Costs	-0.217
	Other Farmland	Revenues	-0.121
		Costs	0.102
Lin and Dismukes (2007)	Linear Model	Corn	0.170
		Soybeans	0.295
		Wheat	0.248
	Acreage Share Model	Corn	0.345
		Soybeans	0.304
		Wheat	0.336
Morzuch, Weaver, and Helmberger (1980)	Wheat-Model 1	Kansas	0.410
		National	0.170
	Wheat-Model 2	Kansas	0.320
		National	0.460
Nerlove (1956)- General Method		Wheat	0.930
		Corn	0.180
		Cotton	0.670
Orazem and Miranowski (1994)	Rational Expectations	Corn	0.095
		Soybean	0.332
		Hay	0.180
		Oats	0.812
	Myopic Expectations	Corn	0.099
		Soybean	0.376
		Hay	0.182
		Oats	0.793
Whittaker and Bancroft (1979)		Corn	0.220

Chapter 3 - Theoretical Model

The theoretical section follows the same format as the literature review. Crop allocation is discussed, followed by yield response. Farmers allocate land based on a variety of economic and biophysical factors, discussed in depth below. The decision of allocating acreage to a specific crop is made before the yield function is determined. The profit-maximizing producer will then allocate inputs based on expected plant nutrient requirements, input prices, and output prices throughout the growing season.

Crop Allocation Theory

The theoretical model of crop allocation presented here closely follows the Chavas and Holt (1990) analysis of risk in acreage decisions. Consider a farmer who has a fixed amount of land (A) to allocate between many cropping options. They allocate land such that $\sum_{i=1}^{n} a_i = A$, where *i* indicates a specific crop, $i = 1,2, \ldots, n$. The farmer will allocate land such that total revenue and are be defined by the following equations:

$$R = \sum_{i=1}^{n} PX_i Y_i \, a_i \tag{1}$$

$$C = \sum_{i=1}^{n} c_i a_i \tag{2}$$

Where total revenue (R) is the per unit price (PX) multiplied by the yield per acre (Y) and the number of acres planted (a). The costs (C) are the number of acres planted multiplied by the per acre costs (c_i) of production. Yield is a function of the input prices, output prices, weather, and acres planted. Further discussion of the determinants of expected yield is discussed in the theoretical section of yield responses below. These variables are assumed to be held constant in the acreage allocation model. Costs are defined by the per acre cost (c) of a specific crop, multiplied by the number of acres planted. Fixed costs are ignored for simplicity of analysis.[1] The simplicity of these equations is lost when considering empirical production decisions. Agricultural production decisions are based on expected prices and yields, as actual yields and prices can vary significantly from the time of planting. Some of this difference can be explained by the seasonality of crops, where harvesting can be as far as ten months after planting. The firms, however, are allowed to have perfect knowledge of input prices and per acre costs of each decision at planting. This relationship of unknown revenues emphasizes the importance of understanding the role of expectations in agricultural production decisions.

A budget constraint for the farm household is defined as follows:

$$W + \sum_{i=1}^{n} PX_i Y_i \, a_i - \sum_{i=1}^{n} c_i a_i = G \tag{3}$$

Income (W) is all income earned by the household not in crop production, which is therefore exogenous. Exogenous income and net farm profit are equal to the total off-farm expenditures, defined by the consumption bundle (G). The household thus maximizes expected utility (EU) as a function of consumption. Assuming consumption of normal goods, the marginal affect of G is positive. Substituting the budget constraint into the utility function:

$$Max\colon EU\left(W + \sum_{i=1}^{n} \pi_i \, a_i\right) \tag{4}$$

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[1] This simplification is of only limited concern because a majority of the fixed costs are related to capital purchases. By assuming producers already own the proper capital for all the crops and continue to enter the market, the fixed costs are irrelevant to the acreage decision because the choice to enter the market was made when the capital was purchased.

The per-acre crop-specific profit (π_i) is defined by the revenue per acre minus the cost per acre. All prices and income are assumed to be in real terms to account for inflation. Expected utility is used due to the uncertainty of output prices and yields. Farmers' expected prices are a function of the expected prices at harvest and the expectation of the accuracy of these prices of predicting harvest prices at planting.[2]

Consider the role of land quality in acreage decisions (Segerson, Plantinga and Irwin 2006). Land quality is measured by variable q, which is quantified as a continuous variable, $0 \leq q \leq 1$. Land quality is a function of the site-specific expected weather and soil quality. In a two crop choice model, the farmer will allocate all land to crop 1 over crop 2 if:

$$\pi_1(q) > \pi_2(q) \tag{5}$$

This criterion would result in a corner solution, were all acres are planted to the same profit maximizing crop. Theoretically, if crop 1 is grown on the highest quality, with land quality ranging from q to 1, the acreage planted is equal to

$$a_1 = \int_q^1 g(q)dq \tag{6}$$

With g(q) is equal to the amount of acreage containing quality greater than q. The acreage relegated to other crops is defined as $A - a_1 = \sum_{i=2}^{n} a$. However, with aggregated data and multiple crop varieties, land qualities and nutrient requirements are not homogenous. These differences result in large portions of land being separated into multiple crops. Specific crops are more suited for select weather and production practices. The role of crop rotations also plays a large role in types of land designated for crops. The most profit maximizing crop is different for

[2] Discussion of this principle is presented in the discussion of the variables used.

each climate and location. With climate and weather determining historical and present land qualities, these biophysical measures quantify land quality differences across areas of space. Thus, the planting decisions can be defined by equation 7 below:

$$a_i = f(PX_i, PF, Y, W) \tag{7}$$

Where acreage (a_i) is a function based on the expectations of prices and yields, and weather (W). Land quality is defined as a function of climate and weather. This theoretical section ignores the role of risk which would impact acreage through perceived differences in expected prices and yields and the actual results. Risk would also play a role for the individual farmer looking to mitigate price and yield risk by planting multiple crops.

Yield Response Theory

The theoretical model of yield response is assumed to be independent of crop selection. As expected, revenues are a function of output prices, acreage, and yield; the yield function hold fertilizer, land, and weather constant. However, in an agricultural production function, these variables cannot be held constant, and provide the vital information for explanations into the empirical reasons for variations in yields. The production function of this study closely follows that of Houck and Gallagher (1976).

$$X = f(F, PX_i, A, W) \tag{8}$$

Total output (X) is a function of fertilizer application rates (F), own price of output (PX), and land (A). Weather (W) is a vector of relevant measures of climate and seasonal weather which impact yields and production behavior. The application of fertilizer is a function of its own price (PF), $F = h(PF)$. All other production variables such as inputs, technology, and management capabilities are embedded in the function itself. The function can further be defined by

$$X = g(PF, PX_i, a_i, W) \tag{9}$$

Where total output is a function of the price of fertilizers, the own price of output, weather, and land designated for crop i. This theoretical section limits input costs to fertilizer prices for simplicity of analysis. Input prices are often highly correlated, and analysis of the theoretical impact of other inputs could simply exchange fertilizer prices with another input of choice. The price ratio of input-output prices used by Houck and Gallagher (1976) is not used due to the strict linear assumption that all prices are homogenous of degree zero. This separation provides the specific impact of each price on the actual yield.

The function defined below is the per acre production function.

$$Y = \frac{X}{a} = h(PF, PX_i, a_i, W) \tag{10}$$

Yield is the total output divided by the number of acres in production. Economic theory would predict the marginal impact of input prices on yield to be negative ($\partial Y/\partial PF < 0$), and the marginal effect of output prices to be positive ($\partial Y/\partial PX > 0$). Furthermore the expected relationship of yield and land, is also expected to be negative($\partial Y/\partial A < 0$). As discussed in the acreage model, the most profitable acreage for a specific crop is initially allocated to said crop. Each additional acre is of lesser quality than the original acreage used, thus the aggregate yield measure would show an increase of acreage would lower yields. This concept of marginal acreage which follows the Law of Diminishing Marginal Returns, shows expansion of production moves into lesser quality and lower yielding land which impacts overall yield measures.

Weather is treated differently in the yield model due to the seasonal impacts of weather on yields. Weather in the acreage model is a general proxy for land quality and climate. The climate factors impact the types of crops producers deem suitable for the varying land qualities. However, in yield models, farmers base their production decisions on expected climate and actual observed weather. Weather in this model measures the actual seasonal weather, which varies from expected climate and weather patterns. This variance impacts yields greatly. The impacts of the weather and climate variables are presented in the empirical results of this paper.

Derivation of Total Supply Elasticity

The regression results will measure the impacts of the many variables on their respective functions. Many researchers have estimated yield and acreage elasticities with respect to prices, to estimate supply elasticities. By estimating only one of the supply elasticities, the impact of prices on total supply is limited. This section provides the theoretical background of the impact of prices on total supply. Total supply of agricultural products is defined below:

$$TS = Y * A \tag{11}$$

$$A = f(PX) \tag{12}$$

$$Y = g(A(PX), PX) \tag{13}$$

Total supply (TS) is equal to the yield per acre multiplied by total number of acres. The total number of acres is a function of price. Yield is a function of acres and prices.[3] Using total differentiation, the marginal impact of own prices is defined by the following:

$$\frac{\partial TS}{\partial PX} = \frac{\partial TS}{\partial A}\frac{\partial A}{\partial PX} + \frac{\partial TS}{\partial Y}\frac{\partial Y}{\partial PX} + \frac{\partial TS}{\partial Y}\frac{\partial Y}{\partial A}\frac{\partial A}{\partial PX} \tag{14}$$

This function can further be written in total supply-own price elasticity form as such:

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[3] As shown in earlier sections, yield is a function of multiple variables, however, for simplicity of analysis all other variables are assumed to be held constant.

$$\varepsilon_{SR\,TS,PX} = \varepsilon_{A,PX} * \left(1 + \varepsilon_{Y,A}\right) + \varepsilon_{Y,PX} \tag{15}$$

Each elasticity with respect to price is expected to be positive, however $\varepsilon_{Y,A}$ is assumed negative. As discussed earlier, the expected marginal effect of acreage on aggregate yields is expected to be negative. The increase in marginal acres would lower total aggregate yields. A price increase is expected to increase the amount of acreage planted increasing total supply, however the expanded acreage impacts aggregate yields. Thus the yield acreage elasticity is expected to mitigate a portion of the own-price acreage elasticity. The sign of the function is undeterminable, however, empirically the function is expected to be positive. For a negative elasticity the following condition would be true; $\left(-\,\varepsilon_{Y,A}\right) > 1 + \varepsilon_{A,PX}$. This derivation presents total supply elasticity for prices in the short run. Short run elasticities have been used in the research presented earlier (Orazem and Miranowski, 1994; Morzuch, Weaver, and Helmberger, 1980; Lin and Desmukes, 2007).

This analysis will extend the supply elasticities to the long run as well. The short run analysis provides comparatives statics into single year impacts, however agricultural production research has shown a persistence or inability to adapt to prices in the short run due to farmer preferences or crop specific capital. Production theory would state profit maximizing producers produce in the inelastic range of production. Producers however in the long run are expected to possess a greater ability to adjust production techniques to varying input and output prices, resulting in higher long run elasticities. Analyzing short run impacts of prices would underestimate the impact of prices on production behavior.

Following Nerlove's (1958) estimation of long run supply elasticities using distributed lags, long run supply elasticities are estimated. He discussed the concept were distributed lags measure producers' aversion or inability to switching crops holding all other things constant.

Lagged acreage variables measure the portion of acreage to be planted due to previous production decisions. Conversely if changes in variables impact production decisions in the short run those effects are shown in subsequent acreage allocation decisions. Short run estimates do not account for the impact on future production. This is an important part of the analysis due to varying adoption rates as well as other reasons which limit short run production changes, such as capital purchases. Using Nerlove's method the following is the long run supply elasticity:

$$\varepsilon_{LR\,TS,PX} = \frac{\varepsilon_{A,PX}}{1-\varepsilon_{A,LA}} * \left(1 + \varepsilon_{Y,A}\right) + \varepsilon_{Y,PX} \tag{16}$$

This formula accounts for the long term impact of a change in prices. Where the lagged acreage elasticity measures the percent change in acreage in the current year over the percent change in acreage from the previous year. This elasticity, $\varepsilon_{A,LA}$, is assumed to be less than one. An elasticity greater than one would assume a continuously increasing acreage function holding all other variables constant. This result would contradict theory and would likely be due to the omission of relevant variables. The total supply elasticity with respect to input price is estimated identically, by switching output with input prices. Production theory would suggest that the total supply elasticity with respect to input prices is negative. The results section of this paper will attempt to estimate all of these elasticities and marginal effects. The results section will also discuss potential reasons for the elasticity estimator to be over or underestimating the true elasticities.

Chapter 4 - Data and Empirical Model

The economic and mathematical models used for land use decisions have varied significantly by researcher and statistical software available. The specific models used have depended on the parameters of interest and focus of research. The models themselves have also varied among researchers. This section focuses on the empirical models used and the reasoning behind selecting each model as a tool for analysis in this study. The advantages and disadvantages of these models are presented below. The following section discusses the data sets and variables used in this study.

Econometric Models Used

Three econometric models were used in this research to analyze the supply response of aggregated producers: Ordinary Least Squares (OLS), Fixed Effects model (FE), and Seemingly Unrelated Regression (SUR). The OLS model is the simplest model presented, where the error term is assumed to follow a normal distribution and uncorrelated over time. The model is presented as follows:

$$y_i = \beta_1 + \sum_{j=2}^{J} \beta_j X_{ji} + e_i \qquad (17)$$

Where y is the output (dependent variable) and X the vector of all relevant independent variables; i=1,2,..N refers to a specific crop, and j=1,2,..J is specific to each independent variable. The constant term β_1, is the point of output holding all other variables constant at zero. This model assumes that there is no correlation among errors over time. The benefit of the OLS method is that it measures and accounts for the between-county responses to the independent variables.

The Fixed Effects (FE) model is similar to the OLS, except in how it treats the constant term and pooling of dependent variables. The OLS assumption that all error terms are not correlated among each observation can prove to be unrealistic in panel level data. Empirically for county t, the error term is often correlated between years. The FE method accounts for the correlation of the error term through pooling variables. The FE model empirically used in this research pools data by county to measure the within county variation. This pooling method accounts for heterogeneous land qualities, production techniques, and other important variables which may vary across specific counties. The OLS method ignores these categorical differences across counties. Presented below is the FE model.

$$y_{it} = \beta_{1,it} + \sum_{j=2}^{N} \beta_j X_{jit} + u_t + e_{it} \tag{18}$$

The model follows the same procedure as listed earlier; however the constant term is specific to a set of pooled data, specifically county t. As opposed to accounting for the county-specific production capabilities through dummy variables, which can be done through OLS, the production prowess of each county is in the coefficient of their respective constant term. The FE model however is limited in its' ability to measure changes within a specific county over time. One method used to account for the changes over time is by creating a binary time variable which attempt to quantify such change. Further discussion of time variables is presented in the latter portion of this chapter. A disadvantage of this method specific to this analysis is due to the data set being cross-sectional dominant, where the numbers of counties are larger than the observations per county. This leads to smaller sampling data sets which decreases the significance of the results.

The third and final model used is the Seemingly Unrelated Regression (SUR). This method is similar to the OLS method presented earlier, except for the expectations of the error terms (Zellner 1962). This model assumes that the error terms are contemporaneously correlated, or correlated within the same time period. Mathematically the covariance matrix of the error term is assumed to be zero in OLS. The SUR model does not make this assumption and accounts for correlation over time among the error terms. The model regresses the four crop equations using OLS. The residual terms are then computed in a covariance matrix, and regressed with all equations using the Generalized Least Squares method. This method theoretically provides more efficient estimators and accounts for variances across each crop for a given year. Empirically this may be important due to unquantifiable weather effects or pests which may impact all crops in a given year as well as acreage decisions which may be correlated due to the substitutability of acreage in production.

Each model analyzes the data similarly, however, how the results and marginal effects are interpreted vary. The OLS method provides simplicity of analysis and results which analyze the impact of explanatory variables across counties. The FE model ignores variances between counties and strictly measures the within county response to variables.[4] The SUR model accounts for contemporaneous correlation by regressing all equations simultaneously, while accounting for the variance/ covariance matrix of error terms not being equal to zero. To account for heteroskedasticity in the OLS and FE models, robust standard errors are used.

Data

The data were obtained through a variety of sources. County-level acreage and yield statistics were acquired from the National Agricultural Statistics Service (NASS, Quick Stats

[4] Random Effects (RE) models were tested to ensure correct specification for panel data. Implicitly the FE model would best suit the county level data, Hausman tests were conducted to ensure correctness. These results provided evidence for retaining FE models over RE (Maddala and Lahiri 2009).

2.0). The crops of interest for this study are corn, soybean, sorghum, and wheat. These four crops accounted for approximately 87.2% of all acres harvested in Kansas in 2009 (U.S. Department of Agriculture, Kansas Farm Facts 2010 n.d.). The statistics measure the acreage and yield in the harvesting year.[5]

The research presented here involves the use of two separate data sets due to the requirements of the econometric techniques. The OLS and FE models do not require the same number of observations for all crops throughout the time period of analysis. Fully consistent data has no missing values throughout the time period of analysis. Ideally the most consistent data is sought, however when analyzing larger periods of time and area, complete consistency is not possible. This allows the data to cover 104 counties within the state of Kansas.[6] Due to inconsistencies in the NASS county level data, the data is restricted to 1975 to 2007. The inconsistencies are due to insufficient size or confidential data. As expected, the data is not 100% consistent across all counties over time, which is of limited importance to the OLS and FE techniques. However, the SUR technique simultaneously regresses all four equations, which requires the same number of observations for all four crops. To meet these conditions the SUR model is restricted to only counties that plant all four crops consistently across the whole time period. These conditions limit the sample to 51 counties, from 1977 to 2007.[7]

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[5] Wheat is planted in the prior year; i.e. planted in 1985, but acreage/yield is measured in 1986.

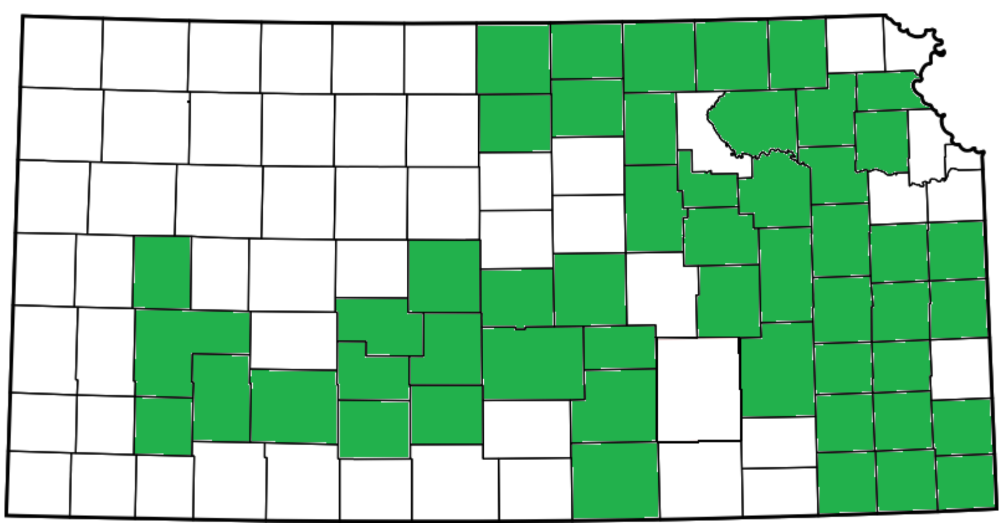
[6] Wynadotte is the only county omitted from the data due to unavailable weather data and inconsistent data in other variables. Concerns of omitting this county are limited due to the location of the county being regarded as an urban area near Kansas City.

[7]Counties included: Allen, Anderson, Atchinson, Barton, Chase, Cherokee, Clay, Cloud, Coffey, Crawford, Dickinson, Edwards, Finney, Ford, Franklin, Geary, Gray, Greenwood, Harvey, Haskell, Jackson, Jefferson, Jewell, Kiowa, Labette, Linn, Lyon, Marshall, Miami, Mitchell, Montgomery, Morris, Nemaha, Neosho, Osage, Pawnee,

[7] Continued: Pottawtomie, Pratt, Reno, Republic, Rice, Scott, Sedgwick, Shawnee, Stafford, Sumner, Wabaunsee, Washington, Wilson, and Woodson

The SUR provides a different perspective for the acreage and yield response functions. The ability for direct comparisons between that and the OLS and FE data set is limited. With the counties restricted potential sample bias is directly apparent. Since the SUR data is restricted to counties which already produce all four crops over the whole time horizon, the expected substitutability of crops would be anticipated to be higher in this data sample. This higher substitutability of crops would likely overestimate price responses in the acreage models. This may present more rigorous econometric results, but the sampling bias limits the replication of the results to other areas. Furthermore, the location of the counties selected increases the consideration for sampling bias. Figure 4.1 highlights the included counties. Initial inspection shows the counties selected are more likely to be eastern counties with higher precipitation and varying soil qualities then that of the western counties.

Figure 4.1. Kansas Counties Selected for the SUR Model



As an economic model, prices are an important factor in cropping decisions. However, as an agricultural model, prices may vary from planting to harvesting. The role of price expectations is more realistic than harvested prices. Many researchers have used lagged pricing as a form of price expectations for planting decisions. However, this method ignores the large commodity futures market. The futures market has directly allowed farmers to enter forward contracts, and fix their output prices throughout all production phases. These contracts allow for established prices, mitigating any risk over the season. These markets also play a role for farmers in the cash market, as the prices often signal expected demand/supply relationships and any general trend within agricultural markets which a lagged price attempts to capture. The use of futures prices has been used by multiple previous researchers (Gardner, 1976; Morzuch, Weaver, and Helmberger, 1980; Orazem and Miranowski, 1994). Before fully analyzing crop prices, it is important to investigate planting time periods.

The prices used in this study are for two different time frames. The month of March plays a critical role in the planting decisions for corn, soybeans, and sorghum. Corn is planted the earliest of the three crops, with planting beginning in Western Kansas in late April (Kansas State University Agricultural Experiment Station and Cooperative Extension Service, Corn Production Handbook 2007). Soybeans are planted slightly before sorghum, with suggested planting dates in the early second week of May (Soybean Production Handbook 1997; Sorghum Production Handbook 1998). All three crops' harvest dates are highly dependent on the amount of rainfall and temperatures as they impact the stage of growth in the plants. In some years, harvesting can begin as early as September or as late as November, and in extremely rare occasions December. The six-to-eight month duration from planting to harvesting is an important aspect in looking at prices. March is the month before any crop is planted and plays a critical role in deciding which of the three crops to plant.

The inclusion of wheat complicates this analysis, specifically due to the planting and growing periods for the plant. In Kansas, wheat is planted from early-to-mid September to late

October (Wheat Production Handbook 1997). As the other three crops are harvested, wheat is planted in the western part of the state. Wheat is then harvested in the following calendar year in late June and early July. Thus the month of September plays a critical role in deciding whether to plant wheat.

This study investigates prices in two specific months, March and September. The corn, soybean, and sorghum analysis includes the futures contracts in March. The wheat analysis investigates the relationship of futures prices in September. The spring crop contracts used are the futures prices in March for delivery contracts in December, and November for soybeans and corn/sorghum respectively. Due to insufficient market size, there is no sorghum futures market. Prices were calculated using a function of the corn futures prices. Sorghum cash prices in March were divided by the corn cash prices and then multiplied by the futures prices. This method effectively values the relative market value of sorghum to corn before planting.[8] This technique is not original to this study, and is used often by farmers in their decision making. The corn and soybean prices used are national monthly average futures prices through the Chicago Board of Trade. The wheat prices were obtained through the Kansas City Board of Trade (Kansas City Board of Trade, 2011).

Cash prices are important for producers, especially for those who do not use the futures markets. The difference between the cash price at harvest and the futures contract is called the basis. These prices are also important in analyzing the differences in futures and cash markets. A higher basis price would indicate an increase in prices of the crop over the production season. Variations in the basis can indicate market volatility as well as market trends. For example, an unexpected large increase grain from corn harvested holding demand constant would result in a

[8] This relationship is often due to the high substitutability of corn and sorghum for feed rations.

negative basis, as there is an abundance of grain in the market. This would also result in a positive basis price for competing crops such as soybean, as acreage was shifted away from legume production. Producers would respond to the higher soybean basis resulting in acreage shifts back toward the original level of soybean acreage. The producers' perceptions of the large fluctuations in grain prices, acreage decisions, and the volatility of the market are expected to be quantified through these variables. The cash prices were obtained through Kansas Agricultural Statistics and are reported at the aggregate state level (USDA-Kansas Agricultural Statistics).

Input prices are an important factor of production and decision analysis. This study incorporates input prices through fertilizer price. Nitrogen is a large percent of farmers' expenses (Kansas State Ag Manager, 2011). Prices were obtained through the USDA average U.S. farm prices in the month closest to planting (U.S. Department of Agriculture, Data Sets, Average U.S. Farm Prices of Selected Fertilizers, 1960-2011, 2011).[9] While other fertilizers are used in farming and listed by the USDA, for simplification the price per ton of anhydrous ammonia (NH3) was used. Anhydrous ammonia is commonly used as a nitrogen supplement for crops as it contains the highest percent of nitrogen per pound. A pairwise correlation coefficient matrix was used to estimate the correlation of anhydrous ammonia and the other types of fertilizer.[10] The average correlation coefficient was 0.87, with the lowest equal to 0.75 and the highest value of 0.97. These results indicated that anhydrous ammonia is an efficient price proxy for fertilizer

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[9] For corn, soybeans, and sorghum the months were either March or April depending on which month it was reported. For wheat the prices where September or October through 1994, and April until 2007. After 1994 prices were only recorded in April.

[10] Fertilizers compared included Nitrogen Solutions (30%), Urea 44-46% Nitrogen, Ammonium Nitrate, Sulfate of Ammonium, Super-Phosphate 44-46% phosphate, Diammonium phosphate (18-46-0), Potassium Chloride 60% Potassium.

inputs. Other researchers have used an average annual fertilizer price index created by the USDA; however this variable was omitted due to correlation with other variables.[11]

All prices were recorded as nominal prices and thus were deflated, to 2007 prices to account for inflation. A Producer Price Index (PPI) was obtained through the Bureau of Labor Statistics, which states the PPI "measures the average change over time in the selling prices received by domestic producers for their output" (U.S. Department of Labor n.d.). The PPI index used exclusively, analyzes annual grains prices for farmers.

Land quality across Kansas varies, including availability of irrigation technology. The county level data for the number of acres in irrigation for crops is highly inconsistent within and between counties, rendering the data useless. While this information could provide useful information, it is not without flaws. Acres irrigated are again a generic term, which does not quantify the quality of irrigation technology used or availability/cost of water for irrigation. By including the variable it implies all irrigation technology and land quality are different than non-irrigated acres, when in actuality the differences may be insignificant.

Weather data were restricted to simple biophysical measures, monthly precipitation and monthly mean temperatures. The precipitation data were acquired through the Kansas State Weather Data Library (Kansas State Research and Extension n.d.). The data were consistent throughout the analyzed time period and presented limited missing values. The impact of temperature on crop yields is captured using mean monthly temperature. The data were obtained

[11] Early analysis showed the price was positively correlated with the number of corn acres planted. This relationship follows theory, as the price of fertilizer increase with an increase in demand due to an increase in an input intensive crop such as corn. Furthermore the index is an annual price index and would be different from that of prices before planting. Output prices are also expected to be correlated with input prices to a certain extent.

through the National Climatic Data Center's (NCDC) monthly surface data (National Climatic Data Center n.d.).

The NCDC data were not available at the county level, but at the weather station level. This issue, as well as inconsistencies with the available data required calculations for aggregation and missing values. To aggregate the data, an analysis of each weather station was needed to ensure consistency. All individual stations which reported data from 1965 to 2010 were defined as consistent stations. Counties with one consistent station where measured strictly by the one consistent station. The counties with multiple consistent stations were averaged across those stations. Counties without any consistent stations were averaged across all stations within their respective county, irrespective of consistency.

While this method provided data for every county included, the weather data still presented missing values within the counties. The missing variables accounted for 2.64% of all values for the mean monthly temperature. Ordinary Least Squares (OLS) regression was used to estimate the missing temperature values. By regressing reported temperatures as the dependent variable and binary variables as the independent variables, the estimated coefficients provided accurate historical estimations. The dummy variables were valued one if true and zero if false. In total there were 159 dummy variables and a constant estimator which accounted for the specific month, county, and year of each reported temperature. To account for collinearity of dummy variables, one variable for each specific category was dropped. The dropped variables were quantified through the value of the constant term. With 55,894 observations separate monthly observations, degrees of freedom were not a concern despite the large number of independent variables. The OLS results provided accurate estimators of historical temperatures. The results showed the model closely fit the data the R-squared value was 0.9598.

Acreage Model

The acreage response model is significantly different from the yield response model due to a variety of factors. As discussed in the theoretical section, the role of expectations plays a significant role in determining acreage decisions. Farmers base their decisions on the expected revenue at harvest for each crop. Expected revenue is the predicted yield multiplied by the output price and the acreage planted.

Some research (Morzuch, Weaver, and Helmberger, 1980) has imposed strict homogeneity in prices. The models used in this research do not make those assumptions. By forcing homogeneity of degree zero in prices, if prices were to double respectively, the amount of acreage planted to each crop would not change. This is an important and strict assumption where in the short run, relative price plays a large role in decision making due to large capital purchases, however, this model assumes that farmers do not have to allocate all available land to production. Total acreage is variable, thus the homogeneity restriction is not applied. The restriction is also not considered in this research due to Chavas and Holt's (1990) explanation of the homogeneity restriction not holding empirically due to uncertainty of output prices. The homogeneity of prices is seen as more of a theoretical question, consequently testing prices empirically through a separation of prices provides more insight into acreage decisions. The total amount of land can vary due to expected prices, income, and other factors. The relative prices also do not hold over time as yields and expectations change, the comparative value changes as the productivity of one crop changes.

The acreage model includes the crop's own price as well as two substitute crop prices. All four prices were not included in the model due to the relationship of corn and sorghum prices. The corn, wheat, and soybean models use their own price and the other two substitute crops. The sorghum model includes only soybean and wheat.[12] Table 4.1 presents the names of the variables used and brief descriptions.

[12] Omitting corn prices in the sorghum model is due to the high correlation of these two prices.

Table 4.1. Acreage Model Variables Names and Descriptions

	Dependent Variable
A	Number of Crop Specific Acres Planted within a given county
	Independent Variables
PX	Real Futures price at planting for after harvest delivery for the crop of interest
PS1	Real Futures price at planting for a substitute crop
PS2	Real Futures price at planting for a substitute crop
PF	Price per ton anhydrous ammonia, Wheat- prices in Sep/Oct, Other Crops- Mar/April
LA	Number of crop specific acres planted last year within a given county
YC	Lagged five year rolling average corn yield
YSoy	Lagged five year rolling average soybean yield
YSorgh	Lagged five year rolling average sorghum yield
YW	Lagged five year rolling average wheat yield
BPX	Lagged three year average difference of cash price at harvest from futures price, crop of interest
BPS1	Lagged three year average difference of cash price at harvest from futures price
BPS2	Lagged three year average difference of cash price at harvest from futures price
CP	Ten year average cumulative rainfall during cropping season, inches
CT	Ten year average mean temperature during cropping season, °F
CP^2	CP squared
CT^2	CT squared

An important characteristic of this research is basis prices. With farmers basing their decisions on expected prices through the futures market, the accuracy or trends of the market play a role in expectations. This acreage response model measures a characteristic of the market by examining the lagged rolling three-year average basis for each crop. Basis prices are the difference in cash prices at harvest, from the futures contracts purchased. By measuring this difference, it shows if futures prices have historically over- or under-valued crops at planting. With the large volatility in commodity markets recently, if farmers perceive a trend of futures prices undervaluing their crops, they may not enter futures contracts but may continue with planting based on their assumption prices for their crop will increase during production. By adding basis prices in this research it is attempting to quantify the producers' valuation of futures prices. The average lagged basis prices show past trends in crop pricing and may explain production decisions not shown in tradition or future prices.

Lagged acreage is included to measure unaccountable reasons for cropping not sensitive to prices or implied stationary cropping practices. This is important to analyze how farmers are resisting acreage short run change due to habit, persistence, or other factors. Crop rotations also play an important aspect of acreage decisions, measuring rotations on an aggregate scale however is not possible. The decision to rotate crops is a sight specific variable which could not be measured by acreage lagged, yield, or any other variable. Expected input prices are generalized through the price of anhydrous ammonia.

The impact of climate plays a critical role in the type of crops planted. Weather in the acreage model is irrelevant to those years' decisions because decisions are made before any seasonal weather occurs. Climate is measured the same as in the yield model. Climate in the acreage model is quadratic to account for nonlinearities. Seasonal weather is accounted for through the yield expectations. Yield expectations are measured as a lagged five-year rolling average of the bushels produced per acre within the county. A five year rolling average was used because it was small enough to measure changes in expected yields due to technology over time but large enough where one bad season would not greatly affect expectations. Increases in seed genetics that result in better drought resistance lessen the impact of weather fluctuations, and are quantified in the yield expectation over time. Other researchers have included integer time variables to attempt to measure technology increases, the expected yield variable can quantify much of the increases in technology over time.

The OLS regression for the yield equation is presented below:

$$A_i = \beta_{1,i} + \beta_{2,i}PX_i + \beta_{3,i}PS1_i + \beta_{4,i}PS2_i + \beta_{5,i}PF + \beta_{6,i}LA_i + \beta_{7,i}YC_i + \beta_{8,i}YSOY_i + \beta_{9,i}YSorgh_i + \beta_{10,i}YW_i + \beta_{11,i}BPX_i + \beta_{12,i}BPS1_i + \beta_{13,i}BPS2_i + \beta_{14,i}CP_i + \beta_{15,i}CT_i + \beta_{16,i}{CP_i}^2 + \beta_{17,i}{CT_i}^2 + e_i$$

This equation presents the relevant variables discussed in both the theoretical and empirical sections. This OLS equation is selected to present the empirical equation, for simplicity. The SUR and FE models are similar except in their assumptions of the correlation of the error terms. Thus the equation is fundamentally similar. Estimating these acreage coefficients provide only half of the total supply equation. The yield portion of supply response is presented in the following chapter. Own prices and fertilizer prices are the same in both yield and acreage response models. Climate variables are also measured similar in both models. By creating partial symmetry between the models allows estimates for the impacts of specific variables on total supply.

Table 4.2. Mean Statistics for the Acreage Model[13]

	OLS and Fixed Effects Data Set				SUR Data Set			
Variable	**Corn**	**Soybeans**	**Sorghum**	**Wheat**	**Corn**	**Soybeans**	**Sorghum**	**Wheat**
A	22.84	23.69	37.36	106.00	22.49	32.33	39.92	101.95
PX	4.00	9.43	3.50	5.29	4.02	9.52	3.52	5.30
PS1	5.25	5.25	5.25	3.71	5.24	5.24	5.24	3.72
PS2	9.44	4.00	9.43	9.25	9.52	4.02	9.52	9.25
NH3	405.17	403.97	404.70	382.24	409.31	409.31	409.31	381.28
LA	22.15	23.13	37.86	106.85	22.01	31.54	40.66	102.69
YC	104.57	104.21	104.46	104.19	102.17	102.17	102.17	100.90
YSOY	30.28	30.20	30.25	30.17	29.26	29.26	29.26	28.94
YSorgh	63.25	63.33	63.15	63.15	64.97	64.97	64.97	64.51
YW	35.38	35.38	35.35	35.49	35.28	35.28	35.28	35.28
BPX	-0.34	-0.68	-0.33	-0.71	-0.37	-0.71	-0.38	-0.72
BPS1	-0.70	-0.70	-0.70	-0.34	-0.72	-0.72	-0.72	-0.34
BPS2	-0.68	-0.33	-0.68	-0.65	-0.71	-0.37	-0.71	-0.64
CP	28.64	27.73	27.61	34.23	30.84	29.73	29.73	36.76
CT	59.56	62.34	62.34	56.75	59.57	62.37	62.37	57.05
CP^2	820.32	769.23	762.35	1172.02	950.99	883.59	883.59	1350.93
CT^2	3547.33	3885.65	3885.72	3220.27	3548.63	3889.57	3889.57	3254.54
Obs.	2784	2674	2796	2732	1581	1581	1581	1581

[13] Own implies the crop specified by the model. The substitutes are defined by the specific model: Corn Model- Wheat, Soybeans; Soybeans- Wheat, Corn; Sorghum- Wheat, Soybeans; Wheat-Corn, Soybeans. For complete descriptive statistics including standard deviations, observations, and minimum and maximum values see Appendix A.

Yield Model

The yield model attempts to measure the impact of economic and biophysical variables on the dependent aggregate yield measures. The independent variables can be broken down into two categories, economic and agronomic. Following the theoretical section, fertilizer price and own price have been separated into their own variables. Houck and Gallagher (1976) used a single fertilizer price over own price, restricting prices to be homogenous of degree zero. As discussed in the acreage model the empirical reasons are similar for the yield model, thus restrictions are not used in the yield model either. By separating the price variables it provides more insight empirically into the specific prices and places no homogeneity restriction. Table 4.3 presents the variables used to estimate crop yields.

Table 4.3. Yield Model Variable Names and Descriptions

	Dependent Variable
Y	Bushels of grain harvested per acre
	Independent Variables
T	Annual time trend
T^2	Time squared
PF	Price per ton anhydrous ammonia, Wheat- prices in Sep/Oct, Other Crops-Mar/April
PX	Futures price at planting for after harvest delivery of the crop of interest
A	Number of Crop Specific Acres Planted within a given county, measured in 1,000s
A%	Number of acres planted to specific crop divided by sum acres of corn, wheat, sorghum, and soybeans
CT	Lagged ten year average mean temperature during crop season; pre, plant, grow, harvest; Units measured in °F
CP	Lagged ten year average cumulative rainfall during crop season; pre, plant, grow, harvest; Units measured in inches
WP	Difference of actual in season rainfall and expected climate rainfall; Indexed i=1,2,3,4[14]; Units measured in inches
WT	Difference of actual in season mean temperature and expected climate temperature; Indexed i=1,2,3,4; Units measured in °F
WP^2	WP Squared
WT^2	WT Squared

To account for land quality, and the concept of marginal acres, acreage has been measured as the percent of all acres with a county of a specific crop and the actual acreage of the crop within the county. The concept of marginal acres implies that as output prices increase farmers introduce lower quality land into production, decreasing aggregated yield measures. The time trend is included to estimate any unexplained systematic difference in yield over time that is not captured through other variables. This includes growth in technology, farming practices, and/or seed genetics. The function is quadratic as it allows for nonlinearity. This flexibility

[14] Wheat is index i=1,2,3,4,5. All other crops are indexed as stated.

allows for the observation of increasing or decreasing marginal returns, as well as yield maximizing optimums.

The biophysical measures are the county level temperature and precipitation. Each crop is produced during specific growing seasons and conditions. Various climates and weather conditions impact these yields. The timing of weather also plays a critical role in the health of plants. Plant yields react differently to a 90°F day in June than they might to the same temperature in October due to the physical stages of growth. One measure of how plants react to temperature and precipitation is measured through how much they transpire. The rate at which plants transpire depends largely on the type of plant and the period of growth. When plants are small, evaporation of water from the soil is a large factor of production. This interaction is smaller when the plants have grown, however they now have higher levels of water transpiration through their leaves.

Aggregated measures of yields and weather have significant limitations in explaining complex biophysical interactions. Complex measures such as evapotranspiration (ET), which measures the amount of water evaporated from the soil and the plant, are highly sensitive to location measures such as daily temperatures, wind speed, soil moisture, air humidity, and rainfall. While these biophysical measures are imperative for analyzing the impact of weather on site specific yield variances, the statistical success of quantifying these measures when analyzing aggregate response is limited. Although the analysis is limited to much simpler weather variables, it is expected these variables integrate the complicated biophysical interactions of weather on crop production.

The model used in this research is restricted to mean monthly temperature and total monthly precipitation. These measures are then aggregated across specific periods in plant growth. The first period of growth analyzed is the sum inches of precipitation in the two months before planting. The second period is the sum inches of rainfall in the two months typically associated with planting. The following period, is the sum rainfall in the months between planting and harvesting. The last period is the sum rainfall in the expected harvesting months.[15] Temperature is measured through the same growing periods however the monthly numbers are not cumulative but averaged.

Wheat is again treated differently, due to the distinct differences in growing seasons of wheat. With wheat planted in September/October and harvested the following June/July the role of winter plays a critical role in the growth of the plant. There are various reasons for late or early planting, however in the winter months the crops freeze, laying dormant until warmer spring temperatures. For this reason the months between planting and harvesting are separated into two different periods, 3 and 4. Table 4.4 below is a chart showing the exact months used to define the periods for each crop.

Table 4.4. Growing Season Variable Definitions

Crop	1	2	3	4	4(5) [16]
Corn	Feb-Mar	Apr-May	Jun-Aug		Sep-Nov
Sorghum	Mar-Apr	May-Jun	Jul-Aug		Sep-Nov
Soybeans	Mar-Apr	May-Jun	Jul-Aug		Sep-Nov
Wheat	Jul-Aug	Sep-Oct	Nov-Feb	Mar-May	Jun-Jul

With the given growing season variables, the model measures the impacts of expected climate and weather. The expected climate is the ten-year rolling average lagged one year

[15] The terms "pre," "plant," "grow," and "harvest" are used throughout the paper as general terms to indicate the specific periods of growth. They are in no way the exact period of which these processes happen every year; rather it is a cleverless way of separating the growth stages of the crops in four distinct stages and provides more explanation then the simple numbering of periods.

[16] The harvesting period is period 4 for corn, sorghum, and soybeans, while it is period 5 for wheat production.

precipitation and temperature for the county. The year variables are measured not in calendar months, but the two months prior to planting through harvesting. The climate variables are expected to capture the expected production practices of a farmer. Farmers would theoretically base early decisions such as irrigation based on expected climate. Weather is measured by the difference in actual weather for the specific season from the expected climate. These variables are also quadratic due to expected nonlinear marginal returns of weather inputs. Land quality and irrigation technologies across all acres are highly variable; however a change in the expected weather is uncontrollable for every producer. While the ability to react to variations in expected weather may differ, these differences are expected to be smaller than the ability to prepare for a specific climate. Thus variables used measure climate and the difference from the climate as opposed to simply the seasonal weather. The equation for the OLS is presented below:[17]

$$Y_i = \beta_{1,i} + \beta_{2,i}T_i + \beta_{3,i}{T_i}^2 + \beta_{4,i}PX_i + \beta_{5,i}PF + \beta_{6,i}A_i + \beta_{7,i}A\%_i + \sum_{k=8}^{11}\sum_{j=1}^{4}\beta_{k,i,j}CT_{i,j}$$
$$+ \sum_{k=12}^{15}\sum_{j=1}^{4}\beta_{k,i,j}CP_{i,j} + \sum_{k=16}^{19}\sum_{j=1}^{4}\beta_{k,i,j}WP_{i,j} + \sum_{k=20}^{23}\sum_{j=1}^{4}\beta_{k,i,j}WT_{i,j}$$
$$+ \sum_{k=24}^{27}\sum_{j=1}^{4}\beta_{k,i,j}{WP^2}_{i,j} + \sum_{k=28}^{31}\sum_{j=1}^{4}\beta_{k,i,j}{WT^2}_{i,j} + e_i$$

The index, i=1,2,3,4, refers to a specific crop, while index k refers to the specific beta coefficient pertaining to each unique variable. The FE model equation is similar to the OLS. As stated earlier the FE estimates within county variances and cross sectional differences are captured through the county specific constant, β_1. The FE results present the constant variable being equal

[17] In the wheat yield model, the summation of weather variables is five separate season measures for each variable, where j=1, 2, 3, 4, 5 as opposed to j=1, 2, 3, 4 in the other three models. This would also increase the index k by one for every summation, thus increasing total variables in the wheat model equal to 37 independent variables.

to the average of all the county intercept terms.[18] The equation for the SUR is similar to OLS, however, the method of producing the results progress as stated earlier.

The climate variables quantify and pool data much in the same way a FE model does through the use of county specific weather variables. Actual variables are more appealing than dummy variables, because they quantify differences of observation within the sample. These variables however are limited with the incorporation of irrigation technology. Irrigation allows farmers to control a portion of their observed weather and climate which in turns limits the ability of weather variables to quantify the yields differences due to weather. The intercept terms in the FE models quantify production differences between counties not do to the included variables. These variables can quantify differences in the percent of irrigation within counties through higher constant terms, as irrigation significantly increases expected yield levels. By including acreage and percent of total acreage, this quantifies differences due to county sizes and production on the extensive margin.

Table 4.5 provides the summary statistics for the yield model. As discussed earlier, by selecting the same sample for both acreage and yield models the marginal effects of variables can be estimated across production responses. This method also results in comparative statics which incorporate the effects of yield and acreage on commodity supply. The results of the empirical models presented are examined in the following chapter.

[18] The county specific FE constants are presented and discussed in Appendix B.

Table 4.5. Mean Statistics for Yield Models

	OLS/FE				SUR Data Set			
Variable	Corn	Soybean	Sorghum	Wheat	Corn	Soybeans	Sorghum	Wheat
Y	108.179	31.093	64.839	35.884	107.241	30.681	67.517	35.869
T	17.953	17.920	17.896	18.533	16	16	16	16
T2	399.710	398.025	397.699	417.022	256	256	256	256
PF	405.170	403.971	404.700	382.242	409.313	409.313	409.313	381.28
PX	4.003	9.427	3.504	5.287	4.017	9.52	3.523	5.305
A	22.844	23.689	37.363	106.000	22.486	32.333	39.918	101.946
A%	12.370	17.691	19.675	50.390	11.439	21.641	19.268	41.706
CT1	39.238	49.190	49.193	78.434	39.192	49.226	49.226	78.664
CT2	59.218	68.874	68.874	62.818	59.236	68.897	68.897	63.193
CT3	76.872	78.417	78.418	34.825	76.903	78.455	78.455	35.032
CT4				54.239				54.707
CT5	56.021	56.018	56.017	76.596	56.047	56.047	56.047	76.834
CP1	3.275	5.051	5.024	6.974	3.618	5.494	5.494	7.258
CP2	7.109	8.560	8.520	5.350	7.573	9.079	9.079	5.96
CP3	11.152	6.983	6.970	4.679	11.753	7.258	7.258	5.235
CP4				9.398				10.078
CP5	7.106	7.140	7.096	7.833	7.894	7.894	7.894	8.225
WP1	0.022	0.000	-0.009	0.124	0.055	-0.072	-0.072	0.095
WP2	0.006	0.106	0.117	-0.234	0.023	0.326	0.326	-0.38
WP3	0.234	0.110	0.094	-0.116	0.379	0.157	0.157	-0.121
WP4				-0.086				0.032
WP5	-0.368	-0.375	-0.383	0.198	-0.428	-0.428	-0.428	0.249
WT1	-0.157	-0.017	-0.016	0.129	-0.117	-0.369	-0.369	0.173
WT2	0.023	0.023	0.025	-0.005	-0.181	0.028	0.028	0.069
WT3	0.127	0.254	0.240	0.173	0.204	0.4	0.4	0.138
WT4				0.173				0.173
WT5	0.194	0.189	0.192	0.036	0.25	0.25	0.25	0.038
$WP1^2$	3.805	5.433	5.398	14.546	0.003	0.005	0.005	0.009
$WP2^2$	9.265	15.604	15.542	10.116	0.001	0.106	0.106	0.144
$WP3^2$	23.175	14.385	14.274	5.697	0.144	0.025	0.025	0.015
$WP4^2$				10.928				0.001
$WP5^2$	13.040	13.137	13.051	16.013	0.183	0.183	0.183	0.062
$WT1^2$	13.518	8.627	8.659	6.282	0.014	0.136	0.136	0.03
$WT2^2$	7.044	5.298	5.300	4.609	0.033	0.001	0.001	0.005
$WT3^2$	4.257	6.050	6.033	9.102	0.042	0.16	0.16	0.019
$WT4^2$				6.268				0.03
$WT5^2$	4.310	4.300	4.297	4.895	0.062	0.062	0.062	0.001
Obs.	2784	2674	2796	2732	1581	1581	1581	1581

Chapter 5 - Results

This section presents the econometric results of the models for the acreage and yield response functions. The models explained a large portion of the variability in yield and acreages. Prices were found to be statistically significant determinants in almost all models. The omission of price response through yield functions would exclude a relevant variable of the regression analysis, and underestimate total supply responses. The weather and climate variables were significant determinants in all models. The potential correlation with climate and lagged acreage is discussed in more detail below.

Acreage Response

The results of the acreage response regressions are presented in tables 5.1 through 5.4 below:

Table 5.1. Regression Results Corn Acreage Response[19]

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
PX	0.986	3.20	0.00	1.529	4.73	0.00	0.985	2.49	0.01
PS1	0.161	0.76	0.45	0.060	0.27	0.79	0.390	2.42	0.02
PS2	0.163	1.34	0.18	-0.026	-0.20	0.84	-0.496	-1.63	0.10
PF	0.003	2.69	0.01	0.004	3.06	0.00	0.004	2.64	0.01
LA	0.985	98.36	0.00	0.926	46.53	0.00	0.947	128.44	0.00
YC	0.014	2.03	0.04	0.051	5.17	0.00	0.033	3.78	0.00
Ysoy	0.058	2.14	0.03	0.063	1.79	0.07	0.045	1.47	0.14
Ysorgh	0.005	0.35	0.73	-0.012	-0.57	0.57	0.047	3.24	0.00
YW	-0.005	-0.18	0.86	-0.054	-1.57	0.12	0.003	0.10	0.92
BPX	2.546	4.53	0.00	2.076	3.43	0.00	2.562	3.42	0.00
BPS1	0.698	2.67	0.01	0.599	2.15	0.03	0.200	0.66	0.51
BPS2	-0.803	-3.28	0.00	-0.460	-1.75	0.08	-0.970	-3.19	0.00
CP	-0.310	-2.48	0.01	-0.170	-0.40	0.69	0.012	0.07	0.95
CT	-1.158	-0.36	0.72	-1.802	-0.56	0.58	0.879	0.26	0.79
CP^2	0.006	2.88	0.00	0.004	0.69	0.49	0.001	0.43	0.67
CT^2	0.010	0.36	0.72	0.015	0.56	0.57	-0.007	-0.25	0.80
Constant	28.593	0.30	0.77	45.271	0.47	0.64	-41.071	-0.41	0.68
R-Squared	0.962			0.9644			0.9599		
Obs.	2784			2784			1581		

[19] Substitute prices are wheat and soybean.

Table 5.2. Regression Results Soybean Acreage Response[20]

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
PX	1.252	10.61	0.00	0.981	8.15	0.00	-0.121	-0.21	0.84
PS1	0.126	0.52	0.61	0.092	0.38	0.70	1.704	1.55	0.12
PS2	-1.264	-3.53	0.00	-1.266	-3.63	0.00	-2.632	-1.84	0.07
PF	0.003	2.74	0.01	0.006	5.89	0.00	0.020	4.16	0.00
LA	0.957	110.55	0.00	0.777	36.88	0.00	0.203	7.63	0.00
YC	-0.015	-2.80	0.01	-0.017	-2.11	0.04	-0.121	-3.82	0.00
Ysoy	0.061	2.70	0.01	0.116	4.54	0.00	-0.283	-2.59	0.01
Ysorgh	0.063	6.13	0.00	0.101	7.30	0.00	0.527	9.94	0.00
YW	-0.065	-2.75	0.01	-0.045	-1.51	0.13	0.323	2.73	0.01
BPX	-0.206	-0.78	0.44	0.303	1.20	0.23	-3.044	-1.13	0.26
BPS1	-0.246	-1.00	0.32	0.335	1.34	0.18	2.961	2.72	0.01
BPS2	-0.230	-0.42	0.68	-2.102	-3.80	0.00	0.562	0.51	0.61
CP	0.335	2.99	0.00	-0.967	-3.55	0.00	1.584	2.23	0.03
CT	-3.626	-1.22	0.22	-1.879	-0.67	0.51	-1.159	-0.09	0.93
CP^2	-0.004	-1.94	0.05	0.017	3.55	0.00	0.014	1.12	0.26
CT^2	0.029	1.21	0.23	0.015	0.66	0.51	0.011	0.11	0.91
Constant	97.766	1.07	0.29	63.061	0.72	0.47	-31.910	-0.08	0.93
R-Squared	0.961			0.966			0.575		
Obs.	2764			2764			1581		

[20] Substitute prices are wheat and corn.

Table 5.3. Regression Results Sorghum Acreage Response[21]

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
PX	0.933	2.23	0.03	0.126	0.29	0.77	0.690	1.16	0.25
PS1	0.500	1.41	0.16	0.920	2.59	0.01	0.343	0.68	0.50
PS2	-1.107	-6.48	0.00	-0.844	-5.20	0.00	-0.793	-3.21	0.00
PF	-0.002	-0.99	0.32	-0.001	-0.38	0.70	-0.002	-0.90	0.37
LA	0.912	90.66	0.00	0.001	30.55	0.00	0.926	109.00	0.00
YC	-0.024	-2.20	0.03	-0.106	-6.36	0.00	-0.029	-1.88	0.06
Ysoy	0.068	1.77	0.08	0.224	4.32	0.00	0.058	1.13	0.26
Ysorgh	0.063	2.72	0.01	0.086	3.05	0.00	0.011	0.43	0.67
YW	-0.094	-2.15	0.03	-0.228	-4.77	0.00	-0.015	-0.27	0.79
BPX	6.199	7.56	0.00	7.220	8.14	0.00	6.145	5.95	0.00
BPS1	-4.395	-9.39	0.00	-5.100	-9.92	0.00	-3.312	-6.73	0.00
BPS2	-0.264	-0.82	0.41	-0.386	-1.14	0.25	-1.229	-2.62	0.01
CP	0.801	3.15	0.00	0.942	1.49	0.14	0.147	0.44	0.66
CT	-1.702	-0.35	0.73	-1.946	-0.41	0.68	6.737	1.15	0.25
CP^2	-0.018	-4.10	0.00	-0.016	-1.72	0.09	-0.008	-1.32	0.19
CT^2	0.013	0.33	0.74	0.015	0.39	0.69	-0.056	-1.18	0.24
Constant	55.352	0.37	0.71	68.415	0.47	0.64	-194.902	-1.08	0.28
R-Squared	0.8903			0.9014			0.9168		
Obs.	2796			2796			1581		

[21] Substitute prices are wheat and soybean.

Table 5.4. Regression Results Wheat Acreage Response[22]

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
PX	0.495	1.00	0.32	0.709	1.5	0.134	1.126	1.72	0.09
PS1	0.273	0.34	0.73	4.027	5.42	0	-2.441	-2.32	0.02
PS2	2.278	6.76	0.00	0.407	1.43	0.153	2.970	8.00	0.00
PF	-0.020	-7.47	0.00	-0.032	-11.73	0	-0.023	-5.87	0.00
LA	0.980	160.69	0.00	0.616	26.06	0	0.980	230.03	0.00
YC	0.000	0.01	0.99	-0.083	-4.11	0	0.017	0.23	0.82
Ysoy	-0.018	-0.33	0.74	-0.211	-3.18	0.001	0.338	3.87	0.00
Ysorgh	-0.027	-1.03	0.31	0.007	0.21	0.837	-0.099	-2.48	0.01
YW	0.160	2.78	0.01	0.138	2.13	0.034	0.000	-0.01	0.99
BPX	7.217	18.53	0.00	6.330	17.69	0	7.729	16.01	0.00
BPS1	-18.094	-17.07	0.00	-11.283	-10.91	0	-16.942	-12.46	0.00
BPS2	2.111	3.78	0.00	1.150	2.16	0.031	0.815	1.16	0.25
CP	-0.155	-0.69	0.49	-1.937	-4.33	0	-0.710	-2.05	0.04
CT	-10.990	-1.37	0.17	-30.480	-1.93	0.054	-10.117	-0.74	0.46
CP^2	0.001	0.31	0.76	0.022	3.97	0	0.009	1.87	0.06
CT^2	0.099	1.40	0.16	0.277	1.99	0.047	0.093	0.77	0.44
Constant	288.613	1.28	0.20	916.744	2.04	0.042	268.410	0.70	0.49
R-Squared	0.9821			0.9856			0.9854		
Obs.	2732			2732			1581		

The models fit the acreage allocation models well, with the R-squared values varying from 0.575 to 0.9854.[23] Much of the model fit can be explained by the lagged acres variable. Although this variable is econometrically unappealing, due to the inability to predict behavior beyond past behavior, it is important for analyzing acreage decisions. Producers' inability or unwillingness to respond to price changes is due to a variety of factors including capital purchases and farmer preferences. The omission of the lagged acres in the OLS model would

[22] Substitute prices are corn and soybeans.

[23] The R-squared values were all greater than 0.9 before dividing the dependent variable by 1,000. This does not change the sign or significance of the variable in the OLS and FE models, it simply moves the decimal point of the variables. However in the SUR model, it changes the variance/ covariance matrix, and thus the estimated coefficients. The 0.575 value was a result of this transformation.

decrease the R-squared values significantly to 0.1787, 0.5807, 0.4651, and 0.4268 for sorghum, soybeans, wheat, and corn, respectively. The large decrease in model fit for the sorghum acreage equation is likely explainable to farmer preferences. The lagged acreage may explain a counties acceptance of sorghum as an alternative to the other three crops. Counties which are already producing sorghum have shown an ability to accept the crop as a substitute, while the lack of model fit shows the other variables including price are not the major determinants for farmers planting sorghum. The role of crop rotations may also impact the model fit (Hendricks 2011).

Prices are a significant determinant of acreage decisions. The own prices are statistically significant and positive for all models for corn and soybeans, only OLS for the sorghum model, and positive but not significant at 95% two-tail confidence level for all other wheat and sorghum models. The lack of significance could be due to a multitude of factors. Perhaps the variable itself is insignificant; however, this would contradict economic theory. A more likely result is due to the correlation of price variables. The substitutability of crops in production and consumption leads the prices to be highly correlated. Collinearity in the model would make the standard errors larger and less efficient, but the coefficients would remain unbiased. The corn and soybean own prices have the largest own price coefficients, perhaps due to the high substitutability of production between the two crops.

The strict assumption that each crop is a competitive substitute for the other crops is shown not to hold. The positive cross price coefficients indicate potential interactions between crops. Due to the impact of acreage planted in previous years impact subsequent production, the direct interpretation of the price relationships is complicated. Field-level data would show the impact of prices on crop rotation patterns coupled with soil nutrients levels which would predict the subsequent crops more precisely (Hendricks 2011). However, with aggregate data, positive cross-price signals are likely to indicate an increase in farmers moving to a crop rotation between multiple crops. Thus the positive cross price coefficient for soybeans in the wheat model might be explained by farmers who double crop annually with soybeans in the spring and wheat in the winter. An increase in the soybean price may increase the number of farmers moving away from a strict corn-soybean rotation, to a soybean-wheat double crop.

Examining the relationship of soybean and corn prices further show the complexity of cross prices on acreage. The positive cross price effect of soybeans in the SUR model and insignificant coefficients in the other two models show the multiple interactions the price of soybean has on acreage decisions. Farmers already engaged in corn- soybean rotations are more likely to plant soybeans when there are higher expected revenues from soybeans. Higher soybean prices are also indicative of more farmers entering the corn-soybean rotation, thus planting more corn acres. This interaction also shows the potential correlation of prices due to the high substitutability of the crops planted. The impact of soybean prices impacting producers decisions of double cropping or yearly crop rotations explain much of this complexity. Examining the sorghum model and the cross soybean price, it is clear an increase in soybean price decreases the number of acres of sorghum planted. The increase in soybean price leads to a decrease in sorghum acres, with the latter sorghum acres potentially then being split into double cropping with wheat or rotations with corn.

The lagged three-year average basis prices are significant across most models and crops. The coefficients are statistically significant and positive for corn, wheat, and sorghum own basis prices. When cash prices are greater than the futures prices at harvest, more acreage is in production in the subsequent year. This result implies farmers' perception of the actual cash price at harvest may be different than that of the current spring futures prices. The cross basis prices act much in the same way as the futures prices. The only major difference is in the corn model and soybeans basis prices. The strict negative and statistically significant soybean basis prices show a farmer's decision to rotate in the subsequent season or continue with corn.

The impact of the fertilizer price proxy, anhydrous ammonia, is negative for wheat and sorghum. The effect of fertilizer price on soybeans and corn is statistically positive. The impact on soybeans acres is from the switching away from input-intensive crops to the less input-intensive, soybeans. The positive coefficient in the corn model is likely due to the high positive correlation between fuel, fertilizer, and corn prices. With the substitutability of ethanol and gasoline, the prices are highly correlated.[24] This result is also consistent with other previous research (Huang and Khanna, 2010). Soybeans are also used in farming as long term substitutes to fertilizers for increasing nitrogen levels and soil quality.

The expected own-yield variables were significant and positive across all crops and models.[25] The analysis is less robust across the models for the substitute expected crop yields. The results from the FE effects models follow traditional theory the closest, with most cross yields insignificant or significantly negative. The only difference from that traditional theory was the relationship between soybean and sorghum yields, both were positive in the other respective model's results. This relationship might be explained by the atypical behavior many farmers have with planting sorghum. The success of the FE model is likely due to the pooling of county data. With the FE model measuring the within county variation, the expected yield provides insight into county level production aptitude for each crop. A time variable, often used by many researchers to account for technological progress is expected to be a less efficient variable than

[24] Multiple input prices and indices were examined in the regression; all prices were found to be positively correlated with corn acreage.

[25] The lone statistically insignificant expected own yield was from the sorghum SUR model.

expected yield. Through the expected yield variables it provided valuable information into county specific expectations and technological progress. If technology was focused on increasing seed genetics for dry land production, the impacts of this technology would be limited to this specific production. Thus general time variables would omit important producer expectations and how technology has specifically impacted or not impacted their production decisions.

The climate variables provided insight into the impact of expected annual weather plays in acreage decisions. These variables may account for much of the cross sectional differences across counties. The results for wheat showed drier and colder climates planted more acres of wheat. The FE and OLS sorghum models showed the most number of acres of sorghum where planted in counties with approximately 22 and 29 inches of annual rainfall. Temperature was insignificant across all models for sorghum. The impact of rainfall on soybeans was less robust across the models, however, the counties with greater amounts of rainfall were more likely to plant soybeans than counties with less.[26] Higher expected temperatures for soybeans also negatively impacted acreage. The impact of rainfall on corn acreage resulted in convex functions for all three models. The local minimum for rainfall and corn acreage was approximately 26 inches and 20 inches for the OLS and FE models respectively.[27] This shows the function for rainfall is increasing at an increasing rate. The impact of temperature was insignificant across all corn models. The climate precipitation variables were significant across most models and crops, while the significance of temperature was limited. This result was similar to that of the yield model. The correlation of temperature and precipitation could have decreased the efficiency of the standard errors. Correlation of the climate variables with lagged acreage is also of potential

[26] The OLS and SUR models show increasing acreage with an increase in precipitation, while the FE model shows a negative effect.

[27] The global minimum for the SUR model was below the observed county level annual rainfall.

concern. The reason why farmers planted specific crops last year is likely due to the climate expectations in the previous year. These expectations are likely to change only slightly over time, and this correlation may decrease the significance of the climate variables.

Yield Response

The regression results are presented below in tables 5.5 through 5.8.

Table 5.5. Regression Results Corn Yields

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
T	1.728	6.53	0.00	1.535	6.30	0.00	1.621	5.17	0.00
T^2	-0.022	-2.79	0.01	-0.012	-1.67	0.10	-0.007	-0.66	0.51
PF	-0.030	-4.66	0.00	-0.026	-5.63	0.00	-0.022	-3.05	0.00
PX	4.468	3.62	0.00	3.685	3.71	0.00	4.694	3.63	0.00
A	0.323	8.04	0.00	-0.150	-2.42	0.02	0.141	3.14	0.00
A%	0.256	2.89	0.00	0.449	3.07	0.00	-0.170	-1.70	0.09
CT1	-0.340	-0.87	0.39	-0.242	-0.57	0.57	-0.413	-1.05	0.29
CT2	-1.177	-1.72	0.09	-1.162	-1.52	0.13	-2.410	-3.13	0.00
CT3	-1.648	-2.42	0.02	-0.767	-1.30	0.19	-3.269	-4.07	0.00
CT4	2.538	2.78	0.01	1.856	1.81	0.07	4.610	4.45	0.00
CP1	1.456	1.60	0.11	-1.247	-1.27	0.21	0.155	0.16	0.88
CP2	0.235	0.37	0.71	2.788	4.43	0.00	-0.914	-1.32	0.19
CP3	-2.232	-5.97	0.00	0.624	1.50	0.13	-2.816	-6.52	0.00
CP4	-4.902	-10.13	0.00	-3.426	-6.32	0.00	-6.301	-11.17	0.00
WP1	-0.017	-0.06	0.95	-0.172	-0.74	0.46	0.149	0.56	0.58
WP2	-0.117	-0.62	0.53	-0.042	-0.28	0.78	-0.870	-4.72	0.00
WP3	1.920	16.71	0.00	2.032	22.44	0.00	1.550	12.12	0.00
WP4	0.309	2.09	0.04	0.577	4.42	0.00	0.300	1.72	0.09
WT1	-0.978	-6.92	0.00	-0.477	-1.95	0.05	-0.802	-5.51	0.00
WT2	-1.306	-5.89	0.00	-0.509	-1.65	0.10	-2.175	-8.79	0.00
WT3	0.169	0.69	0.49	0.788	2.28	0.02	-1.124	-3.94	0.00
WT4	-1.720	-7.06	0.00	-0.331	-0.88	0.38	-0.134	-0.45	0.65
$WP1^2$	0.106	1.32	0.19	0.039	0.52	0.60	-0.034	-0.41	0.68
$WP2^2$	-0.053	-1.59	0.11	-0.067	-2.73	0.01	-0.001	-0.05	0.96
$WP3^2$	-0.173	-12.47	0.00	-0.161	-14.58	0.00	-0.139	-9.35	0.00
$WP4^2$	-0.028	-2.09	0.04	-0.041	-3.42	0.00	-0.022	-1.16	0.25
$WT1^2$	-0.079	-2.59	0.01	0.064	1.63	0.10	-0.120	-3.54	0.00
$WT2^2$	-0.001	-0.01	0.99	0.093	1.51	0.13	-0.077	-1.35	0.18
$WT3^2$	0.523	7.94	0.00	0.042	0.55	0.59	0.212	3.01	0.00
$WT4^2$	-0.094	-1.20	0.23	-0.236	-2.60	0.01	-0.292	-3.14	0.00
Constant	194.000	6.36	0.00	117.941	4.39	0.00	319.085	9.06	0.00
R-Squared	0.5679			0.7504			0.6585		
Obs.	2784			2784			1581		

Table 5.6. Regression Results Soybean Yields

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
T	0.745	9.21	0.00	0.838	10.92	0.00	0.745	7.44	0.00
T^2	-0.014	-5.80	0.00	-0.015	-6.83	0.00	-0.016	-4.96	0.00
PF	0.004	1.70	0.09	0.004	2.71	0.01	0.008	3.33	0.00
PX	0.994	7.55	0.00	0.965	8.42	0.00	0.589	3.96	0.00
A	0.012	1.22	0.22	-0.017	-0.90	0.37	-0.031	-2.76	0.01
A%	0.011	0.63	0.53	-0.061	-2.21	0.03	-0.001	-0.06	0.95
CT1	-0.751	-3.13	0.00	-0.437	-1.41	0.16	-0.076	-0.30	0.76
CT2	0.684	2.22	0.03	0.084	0.25	0.81	-0.465	-1.46	0.14
CT3	-0.676	-3.14	0.00	-0.311	-1.30	0.19	-0.270	-1.13	0.26
CT4	0.699	2.66	0.01	0.607	1.71	0.09	0.505	1.57	0.12
CP1	-1.927	-7.54	0.00	-0.552	-1.84	0.07	-1.833	-5.97	0.00
CP2	-0.534	-3.26	0.00	-0.265	-1.53	0.13	-1.373	-7.85	0.00
CP3	0.672	5.14	0.00	1.218	8.13	0.00	0.678	4.24	0.00
CP4	-0.565	-3.60	0.00	-0.037	-0.22	0.83	-0.739	-3.99	0.00
WP1	-0.090	-1.18	0.24	0.020	0.31	0.76	-0.079	-1.01	0.31
WP2	0.174	4.10	0.00	0.147	4.17	0.00	0.028	0.59	0.55
WP3	1.127	22.74	0.00	1.169	27.24	0.00	1.205	21.90	0.00
WP4	0.363	7.93	0.00	0.405	9.86	0.00	0.380	6.77	0.00
WT1	-0.168	-2.61	0.01	0.130	1.35	0.18	-0.128	-1.76	0.08
WT2	-0.171	-2.30	0.02	0.010	0.08	0.94	-0.187	-2.35	0.02
WT3	0.050	0.73	0.47	-0.157	-1.38	0.17	-0.354	-4.40	0.00
WT4	-0.031	-0.40	0.69	0.094	0.78	0.44	0.293	3.02	0.00
$WP1^2$	-0.041	-2.03	0.04	-0.034	-2.00	0.05	0.000	-0.01	0.99
$WP2^2$	-0.016	-3.00	0.00	-0.014	-2.97	0.00	-0.012	-2.01	0.05
$WP3^2$	-0.080	-12.81	0.00	-0.083	-13.90	0.00	-0.074	-10.66	0.00
$WP4^2$	-0.037	-7.98	0.00	-0.036	-8.49	0.00	-0.034	-5.52	0.00
$WT1^2$	-0.017	-0.99	0.32	-0.007	-0.36	0.72	0.018	0.94	0.35
$WT2^2$	0.053	2.78	0.01	0.031	1.16	0.24	-0.032	-1.51	0.13
$WT3^2$	0.060	3.62	0.00	-0.006	-0.29	0.77	0.013	0.71	0.48
$WT4^2$	-0.012	-0.49	0.63	-0.007	-0.22	0.83	-0.067	-2.24	0.03
Constant	31.056	2.85	0.00	17.535	1.84	0.07	70.450	5.78	0.00
R-Squared	0.52			0.6825			0.6287		
Obs.	2756			2764			1581		

Table 5.7. Regression Results Sorghum Yields

	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
T	1.475	8.42	0.00	1.274	8.13	0.00	1.753	8.35	0.00
T^2	-0.033	-6.15	0.00	-0.024	-4.98	0.00	-0.035	-5.11	0.00
PF	-0.005	-1.54	0.12	-0.009	-2.83	0.01	-0.011	-2.23	0.03
PX	6.324	8.13	0.00	6.002	8.39	0.00	6.190	6.47	0.00
A	0.026	1.51	0.13	-0.059	-1.64	0.10	-0.031	-1.50	0.14
A%	-0.083	-1.79	0.07	0.074	0.94	0.35	0.107	1.83	0.07
CT1	-0.518	-1.09	0.28	0.508	0.79	0.43	-0.524	-0.93	0.35
CT2	0.112	0.19	0.85	-0.338	-0.48	0.63	-0.383	-0.55	0.58
CT3	-0.085	-0.21	0.84	-0.060	-0.12	0.91	-0.760	-1.51	0.13
CT4	0.483	0.85	0.39	-0.160	-0.21	0.83	1.572	2.35	0.02
CP1	-1.063	-2.06	0.04	1.864	2.93	0.00	-1.527	-2.25	0.02
CP2	1.234	3.90	0.00	1.547	4.09	0.00	-0.288	-0.75	0.45
CP3	2.182	7.57	0.00	2.023	6.13	0.00	0.847	2.39	0.02
CP4	0.605	2.03	0.04	-1.302	-3.37	0.00	0.842	2.30	0.02
WP1	0.544	3.49	0.00	0.763	5.23	0.00	-0.022	-0.13	0.90
WP2	0.490	5.39	0.00	0.505	6.04	0.00	0.485	4.75	0.00
WP3	2.441	25.65	0.00	2.547	28.70	0.00	2.049	17.67	0.00
WP4	0.664	6.68	0.00	0.458	4.84	0.00	0.702	5.85	0.00
WT1	-0.328	-2.73	0.01	-0.043	-0.23	0.82	-0.299	-1.92	0.06
WT2	-0.231	-1.50	0.13	0.487	1.95	0.05	-0.181	-1.08	0.28
WT3	0.025	0.18	0.86	-0.255	-1.07	0.29	-0.571	-3.34	0.00
WT4	0.315	2.14	0.03	0.754	2.97	0.00	0.415	2.06	0.04
$WP1^2$	-0.098	-2.45	0.01	-0.076	-2.04	0.04	-0.015	-0.35	0.73
$WP2^2$	-0.069	-5.17	0.00	-0.068	-6.00	0.00	-0.058	-4.22	0.00
$WP3^2$	-0.195	-13.23	0.00	-0.217	-14.27	0.00	-0.160	-10.61	0.00
$WP4^2$	-0.045	-5.09	0.00	-0.038	-4.99	0.00	-0.028	-2.19	0.03
$WT1^2$	-0.020	-0.63	0.53	0.035	0.88	0.38	-0.028	-0.68	0.50
$WT2^2$	-0.007	-0.14	0.89	0.044	0.77	0.44	-0.024	-0.51	0.61
$WT3^2$	0.005	0.15	0.88	0.101	2.37	0.02	0.006	0.17	0.86
$WT4^2$	0.042	0.88	0.38	0.035	0.54	0.59	0.018	0.30	0.77
Constant	9.688	0.46	0.65	22.937	1.14	0.25	58.864	2.32	0.02
R-Squared	0.3273			0.4977			0.3402		
Obs.	2796			2796			1581		

Table 5.8. Regression Results Wheat Yields

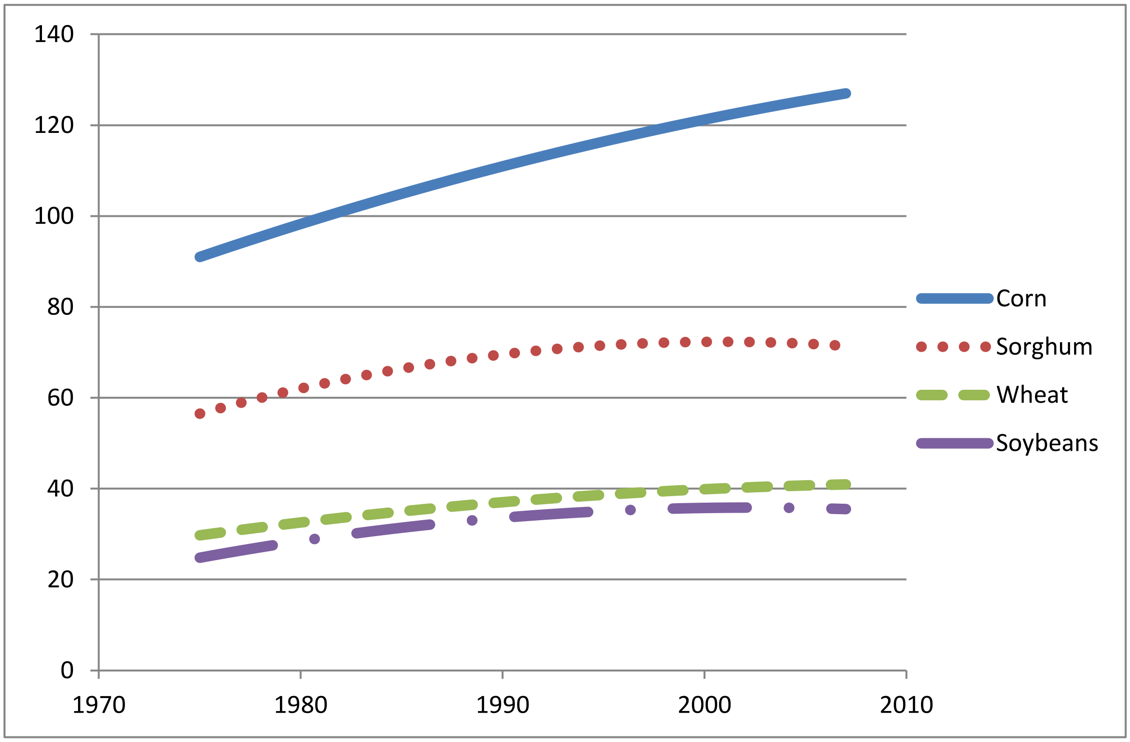
	OLS			FE			SUR		
Variable	**Coef.**	**t**	**P>t**	**Coef.**	**t**	**P>t**	**Coef.**	**z**	**P>t**
T	0.774	5.89	0.00	0.622	4.40	0.00	0.803	5.36	0.00
T^2	-0.012	-3.03	0.00	-0.008	-1.87	0.06	-0.011	-2.35	0.02
PF	-0.007	-2.32	0.02	-0.009	-2.89	0.00	-0.013	-3.52	0.00
PX	4.171	12.80	0.00	3.704	10.39	0.00	4.164	10.64	0.00
A	0.009	3.07	0.00	-0.035	-2.66	0.01	0.000	0.11	0.92
A%	-0.087	-6.19	0.00	0.185	5.00	0.00	-0.025	-1.11	0.27
CT1	0.665	1.16	0.25	1.795	2.69	0.01	1.237	1.69	0.09
CT2	0.947	2.24	0.03	0.878	1.62	0.11	1.801	3.13	0.00
CT3	-0.254	-1.22	0.22	0.340	0.98	0.33	0.252	0.93	0.35
CT4	-1.203	-3.43	0.00	-2.048	-4.55	0.00	-2.681	-5.78	0.00
CT5	-0.306	-0.53	0.60	-1.534	-2.23	0.03	-0.803	-1.07	0.29
CP1	0.118	0.53	0.60	0.768	2.89	0.00	0.589	2.08	0.04
CP2	0.647	2.81	0.01	0.354	1.25	0.21	1.044	3.63	0.00
CP3	-1.126	-4.56	0.00	-1.809	-4.55	0.00	-0.826	-2.81	0.01
CP4	0.688	3.19	0.00	0.769	2.67	0.01	-0.021	-0.08	0.94
CP5	-0.829	-4.16	0.00	-0.659	-2.76	0.01	-0.844	-3.23	0.00
WP1	-0.149	-2.41	0.02	-0.059	-0.96	0.34	-0.040	-0.51	0.61
WP2	0.317	4.44	0.00	0.402	5.51	0.00	0.219	2.56	0.01
WP3	0.047	0.54	0.59	0.042	0.48	0.63	-0.082	-0.83	0.40
WP4	-0.340	-5.54	0.00	-0.369	-5.90	0.00	-0.491	-6.70	0.00
WP5	-0.603	-9.93	0.00	-0.557	-9.15	0.00	-0.579	-7.77	0.00
WT1	0.183	1.77	0.08	0.241	2.18	0.03	0.383	2.84	0.01
WT2	0.223	2.28	0.02	0.197	1.92	0.06	0.402	3.20	0.00
WT3	-0.391	-5.98	0.00	-0.310	-4.63	0.00	-0.360	-4.16	0.00
WT4	-0.815	-10.02	0.00	-0.896	-10.88	0.00	-0.947	-8.94	0.00
WT5	-0.222	-2.12	0.03	-0.186	-1.72	0.09	0.002	0.01	0.99
$WP1^2$	0.016	2.79	0.01	0.014	2.38	0.02	0.010	1.10	0.27
$WP2^2$	-0.042	-5.92	0.00	-0.035	-4.71	0.00	-0.027	-2.85	0.00
$WP3^2$	-0.022	-1.15	0.25	-0.024	-1.30	0.19	-0.004	-0.23	0.82
$WP4^2$	-0.079	-6.75	0.00	-0.078	-6.66	0.00	-0.068	-6.44	0.00
$WP5^2$	0.021	3.09	0.00	0.014	1.95	0.05	0.024	3.12	0.00
$WT1^2$	-0.159	-8.38	0.00	-0.152	-7.78	0.00	-0.161	-6.54	0.00
$WT2^2$	0.150	5.22	0.00	0.161	5.20	0.00	0.043	1.21	0.23
$WT3^2$	0.033	2.17	0.03	0.049	3.21	0.00	0.028	1.39	0.17
$WT4^2$	-0.111	-4.90	0.00	-0.141	-6.22	0.00	-0.051	-1.72	0.09
$WT5^2$	-0.212	-8.52	0.00	-0.190	-7.57	0.00	-0.114	-3.85	0.00
Constant	0.432	0.03	0.97	28.632	1.02	0.31	2.714	0.15	0.88
R-Squared	0.3526			0.4204			0.3937		
Obs.	2732			2732			1581		

The degree of fit of the models varied greatly by crop selected. The corn and soybean models fit the data best. Two of the three sorghum models also fitted the data better than the wheat models. These results show the models tend to fit the spring crops better than wheat. This result is likely due to the complexity of planting and weather patterns involved with wheat. With the dormant period of winter, the complexity of freezing and thawing dates as well as ground precipitation levels, play a large factor in yields. Other possible explanations are the relationship of double cropping with soybeans which impacts the planting dates as well soil nutrients. These factors are difficult to measure or quantify on aggregate levels.

The quadratic time variables present a significant difference in how yields have changed over the period of analysis. Figure 5.1 shows these impacts vary for yield over time. Corn yields have increased significantly over time with the difference of the first year to the final year yield ranging from about to 35 to 46 bushels per acre depending on econometric model selected. Corn yields are still increasing over time while the time variable shows soybean and sorghum yields to have peaked across all models. Depending on the model, wheat yields have already peaked or will peak in the next three years. Soybean yields have increased the least over time followed by wheat, and then sorghum. These results are consistent with the increases in seed genetics and technology for all four crops. To compare the impact of time/technology on yields; corn, wheat, soybeans, and sorghum have increased yields by 40%, 36%, 35%, and 23.7% respectively, holding all else constant.[28]

[28] These numbers are estimated using the estimated yields through the fixed effects models. It is calculated as the difference in yield from 2007 to 1975, divided by the estimated yield in 1975. This method resulted in the percentages presented.

Figure 5.1. Estimated Crop Yields Using Fixed Effects Model over Time[29]



The own price coefficients were positive across all econometric models and crops. When analyzing the prices coefficients, it is unclear whether the yield increases are due to higher quality land or unspecified differences in production behavior, such as weeding or increased pesticide use. Despite any clear indication for either explanation, the results prove the importance of analyzing price in yield response estimates. This result advances the understanding and underlying importance price plays in yield response. The coefficients are largest for sorghum and the smallest for soybeans. Full analysis of the impact of prices is presented in the elasticities section of the results below. Soybeans are a crop which use limited inputs and require the lowest costs per acre of the four crops (Kansas State Ag Manager, 2011).

[29] Yields are estimated using the coefficients and means from the fixed effects model. Coefficients are held constant at the mean for estimation, with an exception for time and time squared.

With limited input use and labor costs relative to the other crops, the ability to adapt production practices to own prices is restricted. To compare the coefficients across the models, they are not statistically significantly different at a 95% confidence level between data sets and models, except for soybeans. The coefficient in the SUR model is statistically lower than that of the complete data set. The explanation behind this result is likely due to the smaller sample used. Although significant, the practical interpretation would show the difference would not dramatically affect yields.

The price of anhydrous ammonia is a significant determinant of yield for all four crops. As a price proxy for all other fertilizers and likely correlated with other input prices the result follows theory. The coefficient is negative for corn, wheat, and sorghum; and positive for soybeans. The impact of fertilizer price is largest for corn which would be expected as corn is the most input intensive crop. Previous research has not analyzed the impact of input prices on soybean yields and the positive coefficient is indicative of potential higher quality acreage shifts toward soybeans. With higher input prices, farmers may switch their higher quality land toward less input-intensive crops. They also switch to planting soybeans to increase future yields of other crops, using soybeans as a long run substitute to fertilizers in seasons with higher fertilizer prices. This substitution is likely most significant in farms who typically apply some variation of a corn-soybean rotation.

The interpretation of the results for own acres and percent of total acreage varies across models. Looking specifically at the OLS models, which do not account for the variations in counties, shows significant positive coefficients. This result is likely due to counties which plant more acres of a select crop are likely to have a comparative advantage of that crop. Although some counties may have higher quality acreage, as stated in the theory section, certain types of land may be more profitable for less profitable crops. This county-level crop specific comparative advantage could be from a shared knowledge of production within county or possible positive returns to scale. In the FE model, which interprets the impact within a county and more accurately measures additional acreage at the margin, shows the number of acres planted to negatively impact yields. With corn and wheat acres significant at 98% and 90% confidence levels, respectively, the impact of marginal acres is evident.[30] As discussed in the theoretical section, crops are planted on land most suited for the specific crop, thus an increase in the acreage of a crop planted would likely be on lesser quality land. With the increases in technology and favorable biofuel policies, corn has expanded acreage throughout the world. This result shows that holding all else constant; the expansion of acreage is decreasing aggregate measures of yields. The acres results in the SUR model should be interpreted much in the same way as the OLS model. These results are mixed, however, in the sign and significance for each crop.

The own acreage percent variable explains a different relationship than acreage itself. Higher land quality is usually used in corn production due to the expected higher level of profits, thus counties with higher percentages of corn are expected to have higher land qualities. The positive coefficient for corn and negative/insignificant for the other crops in the OLS model explains this land quality result. The insignificant soybean coefficient is likely due to the varying qualities of land used for soybeans. The positive coefficients in the FE model could likely be treated as county level comparative advantages for specific crops, much like the acres variable in

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[30] Sorghum and soybean acres were not significant. However this result is expected as these crops are less likely to be planted in more marginal quality land.

the OLS model. The percent of acres planted is not significant at the 95% confidence level for any crop in the SUR model.

In the OLS/SUR model, corn yield decreases in counties with climates that have higher precipitation and temperatures in the planting and growing months, while drier and warmer climates at harvest have higher expected yields. The impact of expected climate in the months preceding planting is limited. In the FE model, only precipitation during planting and harvesting were significant for corn yields. Counties with increases in expected rainfall for planting and decreases in expected rainfall for harvest saw higher corn yields.

Counties with higher expected temperatures and greater rainfall during the planting and preceding months were characterized by higher yields for wheat. The climate during the dormant period of wheat growth is impacted greatly by expected precipitation levels. This result is likely due to the fact counties with higher levels of average snowfall during those months are less suitable for higher wheat yields. Similar to wheat yields; sorghum and soybeans also had higher yields with climates that rained more during the growing seasons. The expected temperatures were insignificant across almost all periods of sorghum growth, but responded positively to higher precipitations levels.

For corn yields, the results show growing and harvesting months are the most important periods for precipitation according to the quadratic weather variables. With yields maximized at 5.5 to 6.3 inches above average in the growing months and about 5 to 7 inches in the harvesting months depending on model interpreted. Corn yields with respect to temperature tend to be higher when temperatures are below their expected climates; however temperatures away from the county average for the growing months are expected to increase corn yields.

Wheat yields were impacted by the weather in slightly different ways. In the planting months slightly higher precipitation increases wheat yields, with global yield maximums at about 4 to 5.5 inches. In the non-dormant growing season yields are highest with below average precipitation. Wheat yields are highest when precipitation is limited during harvesting. This is due to the plants needing to dry out before harvesting. The non-dormant growing season for wheat shows higher yields with colder temperatures, as the global maximums are below zero. Harvesting temperatures are best when they are the expected temperature levels.

Soybean precipitation weather variables were fairly robust across each model. The yield maximizing rainfall in the growing months was about 7 to 8 inches higher than average. The marginal impacts of rainfall were also the greatest during the growing months. Harvesting was maximized with about 5 to 6 inches. Modest increases in rainfall are optimal during the planting season. The interpretation of the impacts of temperature on soybean yields is limited as the results are not robust across the four growing periods or crops. This is likely due to the lack of significance of many of these variables. Discussion of possible reasons for lack of significance is presented later in thesis.

Sorghum yields are impacted by precipitation in much of the same way as soybeans. The impacts of additional precipitation are greatest during the growing months and maximized around 6 to 6.5 inches. Increases in precipitation during the harvesting months also lead to significant increases in yields, with the maximum yields ranging from 6 to 12 inches. Only modest increases of precipitation in the other seasons lead to modest increases in yields. The robustness of the estimators across all models is limited for the temperature weather variables. Increases in temperature during the harvesting months positively impacts sorghum yields. The sorghum grain must reach a certain level of dehydration before optimal harvesting.

With the quadratic variables, the coefficient estimates present concave or convex relationship of the variables on yield. Analyzing the shape of the relationship of variables to yield is important to understanding the sign of the function or marginal return of the variables within the data set sample range. The tables below present the yield maximizing/ minimizing value and descriptive statistics using the FE model. Variables with asterisks indicate concavity and the value is a global maximum.

Table 5.9. Wheat-Yield Maximizing & Minimizing Values of Variables

Quadratic Variable	Max/Min	Obs. Min.	Obs. Max.	Obs. Mean
WT1*	0.79	-8.59	20.58	0.12
WT2	-0.61	-8.79	19.75	-0.23
WT3	3.16	-7.71	12.35	-0.12
WT4*	-3.18	-9.08	16.70	-0.09
WT5*	-0.49	-10.80	19.30	0.20
WP1	2.16	-6.71	8.48	0.13
WP2*	5.68	-6.74	6.32	-0.01
WP3*	0.87	-9.96	6.39	0.17
WP4*	-2.37	-8.53	5.91	0.17
WP5	20.51	-6.36	7.84	0.04
T*	38.88	3.00	33.00	18.53

Table 5.10. Corn-Yield Maximizing & Minimizing Values of Variables

Quadratic Variable	Max/Min	Obs. Min.	Obs. Max.	Obs. Mean
WT1	3.71	-12.01	8.48	-0.16
WT2	2.73	-10.29	6.00	0.02
WT3	-9.32	-6.85	7.15	0.13
WT4*	-0.70	-6.79	6.04	0.19
WP1	2.23	-6.22	9.17	0.02
WP2*	-0.31	-7.70	15.27	0.01
WP3*	6.32	-12.67	23.59	0.23
WP4*	7.03	-12.75	20.30	-0.37
T*	63.62	2.00	33.00	17.95

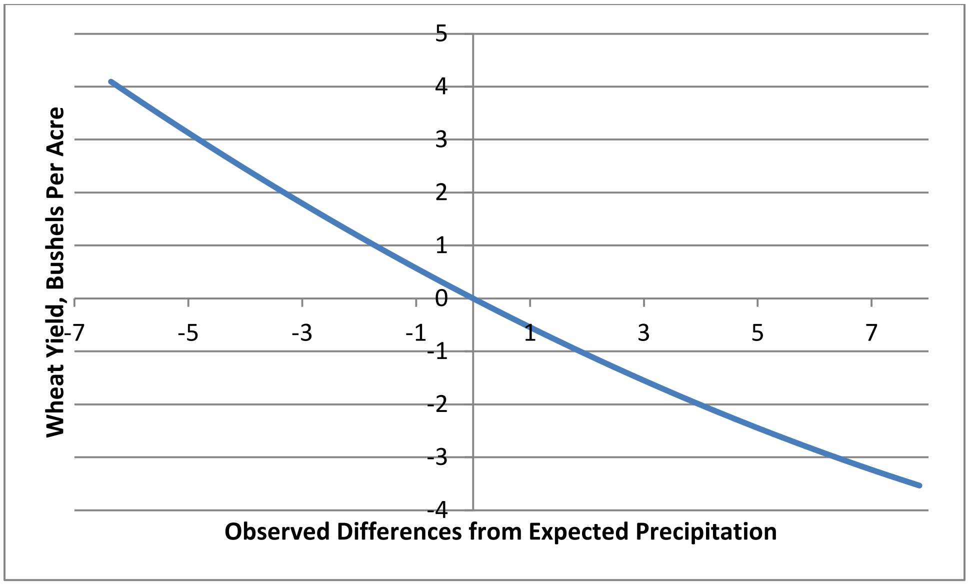
Table 5.11. Sorghum-Yield Maximizing & Minimizing Values of Variables

Quadratic Variable	Max/Min	Obs. Min.	Obs. Max.	Obs. Mean
WT1	0.60	-8.27	6.49	-0.02
WT2	-5.47	-8.83	6.30	0.02
WT3	1.26	-7.14	8.48	0.24
WT4	-10.69	-6.79	6.04	0.19
WP1*	5.03	-7.46	10.94	-0.01
WP2*	3.69	-9.43	17.98	0.12
WP3*	5.88	-8.59	20.58	0.09
WP4*	6.01	-12.75	20.30	-0.38
T*	26.80	2.00	33.00	17.90

Table 5.12. Soybean-Yield Maximizing & Minimizing Values of Variables

Quadratic Variable	Max/Min	Obs. Min.	Obs. Max.	Obs. Mean
WT1*	9.29	-8.27	6.49	-0.02
WT2	-0.16	-8.83	6.30	0.02
WT3*	-12.94	-7.14	8.48	0.25
WT4*	7.14	-6.79	6.04	0.19
WP1*	0.30	-7.46	10.94	0.00
WP2*	5.35	-9.43	17.98	0.11
WP3*	7.08	-8.59	20.58	0.11
WP4*	5.68	-12.75	20.30	-0.38
T*	28.30	2.00	33.00	17.92

Figure 5.2. Effect of Observed Differences from Expected Precipitation during Harvest on Wheat Yields



This method is chosen to present the marginal effects of weather on yields as it more accurately explains the observations in this study. Examining the variable WT5 in table 5.9 and figure 5.2, shows the overall effect of increasing precipitation during harvest is negative on wheat yields. With a minimum value greater than the observed values within the sample, the marginal effect presents a downward sloping convex function which is decreasing at a decreasing rate. Maximum values within the observed data set, show there are optimum levels of weather inputs observed. This is an important statistic for farmers to show the marginal yield changes from precipitation. They can then decide if it is optimal to augment lower precipitation seasons with additional irrigation levels.

The results of climate and weather provide insight into the impacts on crop yields. The lack of significance of many of the variables shows the problem in aggregation over time and county wide. The lack of significance of many of the temperature variables is due to the aggregate mean temperature measure as well as the interaction with precipitation. Months which have higher levels of rainfall also have lower temperatures. The collinearity of weather variables could explain a portion of the higher standard errors. Furthermore plants are affected by temperatures differently during specific periods of growth. A 100°F degree day in June may impact the same crop differently each year depending on maturity and planting dates. The aggregation loses many of these impacts.

Elasticity Results

The elasticity results show the impact of prices on acreage and yields to be in the inelastic range. This short run result is expected, as previous research has shown these results in the ranges shown. Tables 5.13, 5.14, and 5.15 present the price elasticities for the crop in their respective acreage models.

Table 5.13. Own- and Cross-Price Elasticities, OLS Acreage Models, Short Run[31]

	Models			
Crop Price	**Wheat**	**Corn**	**Sorghum**	**Soybeans**
Wheat	0.025	0.022	0.069	0.006
Corn	0.010	0.103^{A}	NA	-0.048^{A}
Sorghum	NA	NA	0.086^{A}	NA
Soybeans	0.199^{A}	0.040	-0.273^{A}	0.112^{A}

[31] The superscript A within the table signifies the marginal effect in the model was statistically significant at 95% confidence level.

Table 5.14. Own- and Cross-Price Elasticities, FE Acreage Models, Short Run

	Models			
Crop Price	**Wheat**	**Corn**	**Sorghum**	**Soybeans**
Wheat	0.036	0.008[A]	0.127[A]	0.005
Corn	0.144[A]	0.161[A]	NA	-0.049[A]
Sorghum	NA	NA	0.012	NA
Soybeans	0.036	-0.007	-0.209[A]	0.089[A]

Table 5.15. Own- and Cross-Price Elasticities, SUR Acreage Models, Short Run[32]

	Models			
Crop Price	**Wheat**	**Corn**	**Sorghum**	**Soybeans**
Wheat	0.059	0.051[A]	0.044	0.088[A]
Corn	-0.090[A]	0.098[A]	NA	-0.104[A]
Sorghum	NA	NA	0.060	NA
Soybeans	0.271[A]	-0.117	-0.187[A]	-0.011

These tables show price elasticities are relatively inelastic. All of the cross price elasticities are not negative in all models as traditional theory may predict. However, some of the positive results are expected due to the nature of cropping patterns discussed earlier. The largest absolute elasticity is only 0.273, indicating prices do not impact production practices greatly in the short run. Corn own-price elasticities are the highest of the four crops in the FE and SUR models, only negligibly smaller than the soybean elasticity in the OLS model. The higher elasticity might be due to the higher production per acre of corn, thus modest changes in prices per bushel greatly impact expected revenues.

[32] The SUR model was also estimated with acreage measured in single digits as opposed to the thousands used in this model. This resulted in marginal effects and elasticities more closely related to the other models. By changing the dependent variable it changed the variance-covariance matrix of error terms for the SUR model. This resulted in a change of the sign and a negative coefficient and elasticity shown here. The sign of the other crops were not affected by the change in classification of the dependent variables.

The total supply elasticity, as derived in the theoretical section, shows the infinitesimal percentage change in quantity supplied given an infinitesimal percent change in price. The total supply estimated here incorporated the effect of prices on supply through a change in acreage, the effect of a change in acreage on yields, and the impact of price on yields. Tables 5.16 -5.18 present the comparative static results for the three econometric models.

Table 5.16. Total Supply Own-Price Elasticities, OLS Models

	$\varepsilon_{A,PX}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PX}$	$\varepsilon_{SR\ TS,PX}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PX}$
Wheat	0.025	0.025	0.560	0.586	0.991	3.319
Corn	0.103	0.065	0.157	0.267	0.970	3.814
Sorghum	0.086	0.013	0.306	0.393	0.905	1.217
Soybean	0.112	0.009	0.277	0.390	0.931	1.900

Table 5.17. Total Supply Own-Price Elasticities, FE Models

	$\varepsilon_{A,PX}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PX}$	$\varepsilon_{SR\ TS,PX}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PX}$
Wheat	0.036	-0.094	0.502	0.535	0.636	0.592
Corn	0.161	-0.030	0.130	0.286	0.908	1.831
Sorghum	0.012	-0.031	0.299	0.310	0.727	0.340
Soybean	0.089	-0.012	0.266	0.354	0.787	0.680

Table 5.18. Total Supply Own-Price Elasticities, SUR Models

	$\varepsilon_{A,PX}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PX}$	$\varepsilon_{SR\ TS,PX}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PX}$
Wheat	0.059	0.001	0.569	0.628	0.994	10.300
Corn	0.098	0.028	0.165	0.266	1.116	-0.702
Sorghum	0.060	-0.017	0.293	0.352	0.933	1.178
Soybean	-0.011	-0.029	0.165	0.154	0.183	0.151

The own price yield elasticities were shown to be much higher in comparison to the acreage models. The elasticities remain in the inelastic portion of production, as shown in the acreage response; however the results are significantly larger than the acreage elasticities. Wheat yields are shown to be the most responsive to price changes, with elasticities ranging from 0.51

to 0.57. Corn yields are the least responsive to price changes, with elasticities approximately equal to 0.17. These results are likely due to corn and wheat having the highest and lowest average revenue per acre planted, respectively.

The total supply results show the omission of yield response when estimating elasticity of total supply would underestimate the values significantly. The yield response is shown to dominate the elasticity, as it is greater than the acreage elasticity for all models. Corn which had the highest acreage response elasticity is dwarfed in the total supply elasticity due to the limited yield response to price. These differences in response confirm the importance of analyzing both effects of acreage and yield on grain supply. Government policies also likely lessened the response of supply from prices for all crops (Morzuch, Weaver, and Helmberger 1980).

The impact of marginal acres on the total supply elasticity is limited. The marginal effects of acreage on yields in the fixed effects model showed the concept of marginal acres clearly. The impact of this acreage on the supply elasticity is however limited. The effect was shown to be largest in the corn model, decreasing the elasticity of total supply by 0.006.

Using the Nerlove's (1958) method for estimating long run supply elasticities they estimated using lagged acreage. The results varied significantly across crops and models. The results show large differences in the elasticities for the four crops and three models. The FE model is likely the most accurate estimator of long run supply elasticities due to the impact of lagged acreage on the elasticity itself. The lagged acreage variable in the OLS and SUR models likely overestimated the impact of lagged acreage on subsequent decisions. This result is due to the assumption of the independence of error terms being violated, and the result can be shown in the marginal coefficients nearly equaling one. The lagged acreage coefficients in the FE are likely statistically more correct. The elastic long run corn supply elasticity is likely overestimated due to the impact of more favorable government policies toward corn production over time, which resulted in a higher lagged acreage elasticity for corn compared to the other crops.

Fertilizer price elasticities can be estimated the same way as own-price elasticities, due to the inclusion of the variable in both models. The estimated impact of fertilizer price on total supply is expected to be negative theoretically. Tables 5.19- 5.21 present the fertilizer elasticity results below.

Table 5.19. Total Supply Fertilizer Price Elasticities, OLS Models

	$\varepsilon_{A,PF}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PF}$	$\varepsilon_{SR\ TS,PF}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PF}$
Wheat	-0.071	0.025	-0.068	-0.141	0.991	-7.976
Corn	0.061	0.065	-0.106	-0.041	0.970	2.047
Sorghum	-0.021	0.013	-0.030	-0.051	0.905	-0.251
Soybean	0.049	0.009	0.042	0.092	0.931	0.761

Table 5.20. Total Supply Fertilizer Price Elasticities, FE Models

	$\varepsilon_{A,PF}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PF}$	$\varepsilon_{SR\ TS,PF}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PF}$
Wheat	-0.116	-0.094	-0.085	-0.191	0.636	-0.375
Corn	0.074	-0.030	-0.095	-0.023	0.908	0.684
Sorghum	-0.008	-0.031	-0.051	-0.060	0.727	-0.081
Soybean	0.113	-0.012	0.004	0.116	0.787	0.530

Table 5.21. Total Supply Fertilizer Price Elasticities, SUR Models

	$\varepsilon_{A,PF}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PF}$	$\varepsilon_{SR\ TS,PF}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PF}$
Wheat	-0.087	0.001	-0.130	-0.217	0.994	-14.411
Corn	0.079	0.028	-0.078	0.004	1.116	-0.778
Sorghum	-0.021	-0.017	-0.058	-0.079	0.933	-0.374
Soybean	0.239	-0.029	0.092	0.324	0.183	0.376

The fertilizer elasticities are negative for eight of the twelve crop models presented. The positive sign of the soybean elasticities is likely due to soybeans being used as a substitute for fertilizer. Soybeans increase the amount of nitrogen in the soil when planted. Furthermore, as a low input-crop, when fertilizer prices are high farmers are more likely to plant soybeans to decrease costs. This relationship explains the positive soybean elasticities. The positive corn elasticity in the SR SUR model and the comparatively small absolute negative elasticity in the OLS and FE models are due to the positive marginal effects of fertilizer price in the acreage model.

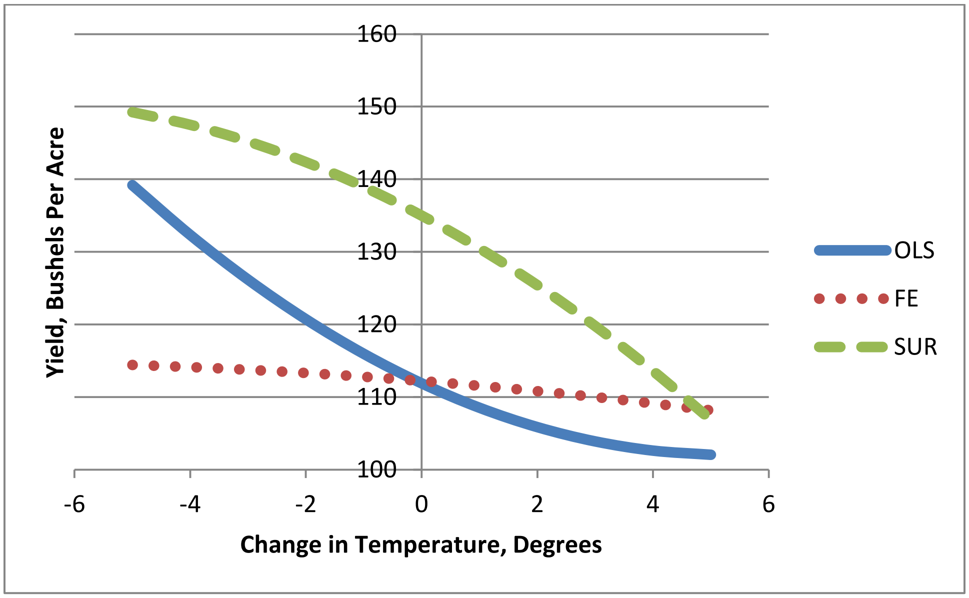
In the FE and OLS models for corn, the lagged acreage elasticity is shown to increase the impact of acreage on the supply elasticity, resulting in acreage effects dominating yield effects with positive long run elasticities. Across models and crops the yield effect tends to dominate the acreage effect in the short run. However, in the long run the acreage is the predominant effect on supply response. As discussed earlier, the reason for a positive marginal effect could be related to the correlation of corn acres planted, and corn and fertilizer prices.

Climate and Weather Simulations

With the weather and climate variables, the results can be estimated further to predict the impact of a change in growing conditions for the state of Kansas. While the predictions of actual climate change are beyond the scope of this analysis, the results do present opportunities to estimate impacts given certain changes to climate and weather. Given the aggregation of the weather and climate data, it would be difficult to effectively estimate changes in weather intensity or variability. Thus the simulations are limited to the quarterly aggregate measures which provide results into annual changes in climate and weather, as opposed to simulations involving daily or weekly weather variations.

The impact of a change in weather during production would dramatically impact the yields of crops. Higher temperatures lower the average crop yields for corn, sorghum, soybean, and wheat yields. Figure 5.4 displays the impact of a change in temperature during the growing season on corn yields.[33]

Figure 5.3. Impact of a Change in Yearly Temperature on Corn Yields



The impact of an increase in temperature would decrease the aggregate yield for corn. A five degree increase in temperature would decrease yields by 11.1%.[34] The effect of a change in temperature on soybean yields is shown in figure 5.5. The average result is expected to be negative from an increase in temperature on soybean yields. This is due to the positive estimated effect of temperature in the FE model. The effect of temperature on sorghum yields is also

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[33] These numbers are estimated for an average change across all four growing periods described earlier in the yield model. All other non-weather temperature variables are held constant at the mean, and temperature is made variable. A one degree increase in temperature is estimated as a one degree increase in temperature for all four periods estimated in the regression. This method was chosen for simplicity. There are a large number of possible combinations that could result in a one degree increase in annual temperature. Further research could look at other possible combinations and their respective impacts.

[34] The difference is calculated as the difference of corn yields with an increase of five degrees and corn yield with no change. These a numbers are then calculated a percentage change from the mean, and then averaged across the three models.

shown to be highly dependent on model selected. Figure 5.6 shows the estimated negative impact of an increase in temperature in the OLS and SUR models on sorghum yields, and a positive estimated impact in the FE model.

Figure 5.4. Impact of a Change in Yearly Temperature on Soybean Yields

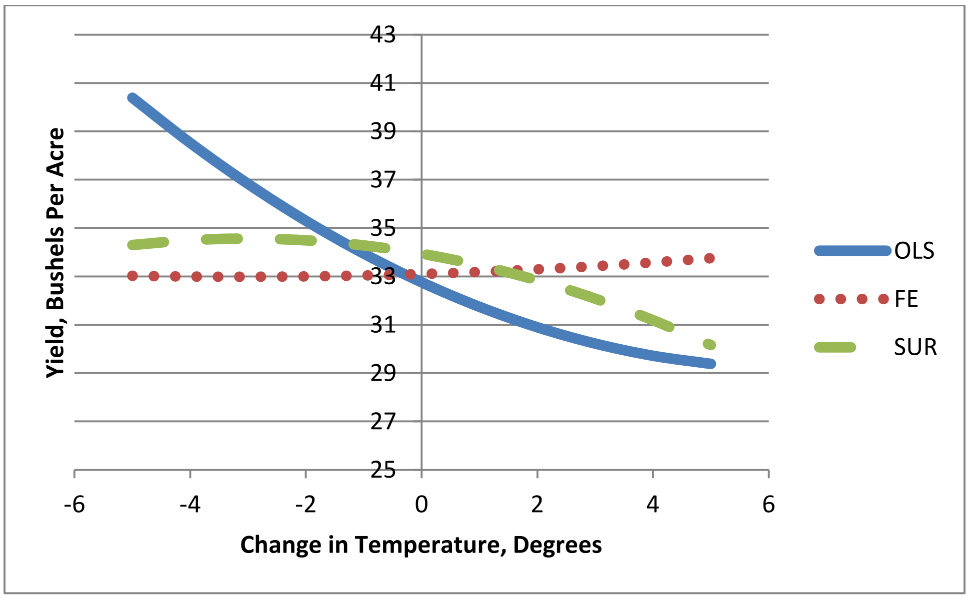
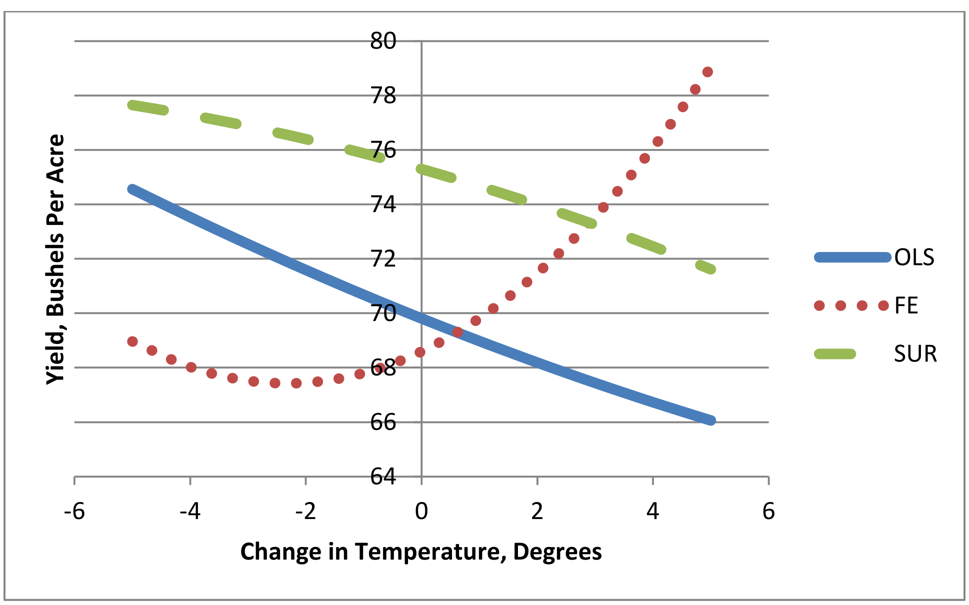
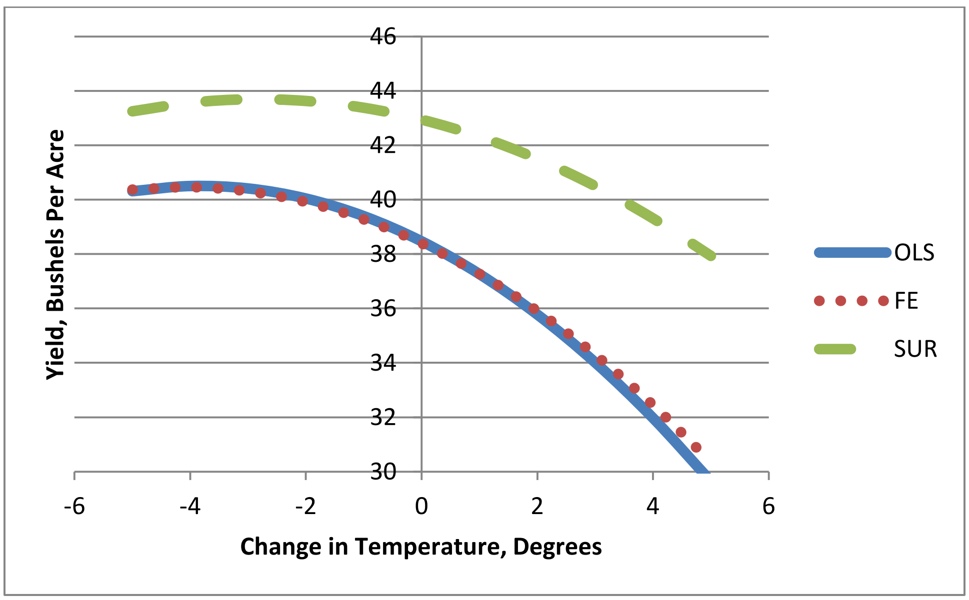


Figure 5.5. Impact of a Change in Yearly Temperature on Sorghum Yields



Wheat yields were estimated to dramatically be impacted by an increase in temperature (figure 5.7). The average estimated impact from a five-degree increase in temperature decreases yields by 18.6%. This decrease shows the high sensitivity of wheat to higher temperatures during the months leading up to and during harvesting. Given the large number of acres of wheat planted in the state of Kansas the effect could considerably affect agricultural county incomes and state tax revenues.

Figure 5.6. Impact of a Change in Yearly Temperature on Wheat Yields[35]



These figures show the effect of temperature changes on yields holding all else constant. An increase in temperature over time would also be met with improved technology and cropping practices. Given the relation of corn yields over time, the negative impact of temperature on yields could be mitigated to a degree by increases in yields from technology. Technological progress is likely to decrease many of the negative impacts. Furthermore, changes in acreage

[35] Since wheat is estimated with five growing periods as opposed to the four for the crops, each period is changed by said measure in each period.

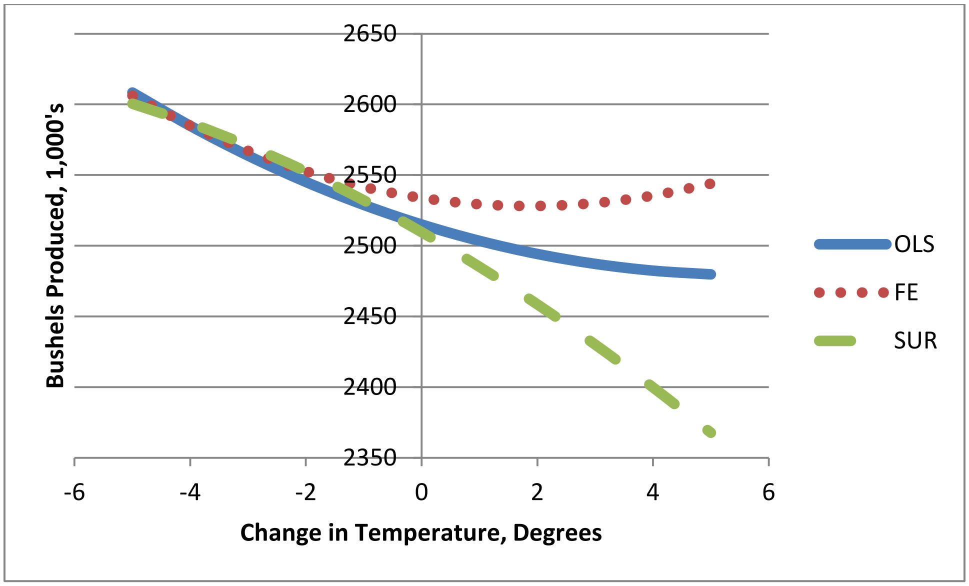
allocation and increases in investment for irrigation also hold great potential to mitigate yield losses. Additional tables for the impact of changes in temperature and precipitation on yields are presented in Appendix B.

The major difference in interpreting changes in weather and climate is the perception of the farmer and their ability to account for changing weather patterns. This importance of farmers' perception of weather patterns impact how changes in weather and climate effect production. If there is a perception the climate is warming and the farmer produces accordingly, the impacts will be different than if the change is not expected. The changes in the weather variables could be explained as short run impacts of a climate change. While the weather impacts on the climate variables would be longer run outcomes.

Estimated effects of a change in temperature on county average bushels supplied are simulated using the regression coefficients. All variables are held constant at their respective mean values, and the climate temperature variables are altered.[36] This is done for both the acreage response and yield response models. The acreage values used in the yield models are from the results of the acreage models. The multiplication of the yield and acreage response estimates provides the mean county impact of a change in climate temperature. Figure 5.8 displays the impact of climate temperature on number of bushels of corn produced.

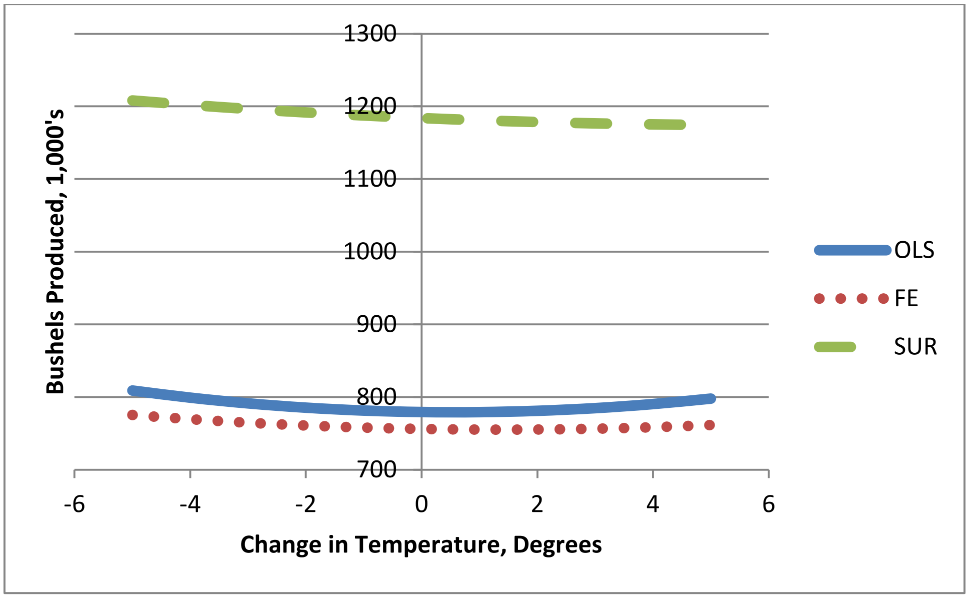
[36] Time is measured in 2007 terms as opposed to at the mean. This was done with the intentions that it provided more recent estimates.

Figure 5.7. Estimated Average County Corn Production with a Change in Climate Temperatures



Averaging the difference of the total bushels produced for a 5 degree increase the temperature results in total bushels produced to decrease by 2.2%. The impact of temperature changes on soybean production was more limited, see figure 5.9. With soybeans tending to be planted in marginal quality soil or in some rotation with other crops, the effect of climate is shown to be limited. With this soybeans are usually not the first choice of crop for producers and are used to increase the yields of subsequent crops or the most suitable crop for that piece of land.

Figure 5.8. Estimated Average County Soybean Production with a Change in Climate Temperatures



The impact of temperature on wheat production is highly quadratic, with temperatures away from the mean increasing total wheat production. A five degree increase in the climate temperature would increase total production on average by 2.0%. These results are shown in figure 5.10. Wheat yields are shown to be increasing with lower temperatures and inversely acreage is increasing with higher temperatures. This effect underscores the importance of analyzing the yield effect of changes in climate as well as acreage shifts. The effect of temperature on sorghum production is expected to be negligible compared to wheat. The FE and OLS models show modest increases from temperature increases, while the SUR shows a strong negative impact. This result is likely due to sampling differences or how the results are estimated differently. Figure 5.11 illustrates the sorghum results.

Figure 5.9. Estimated Average County Wheat Production with a Change in Climate Temperatures

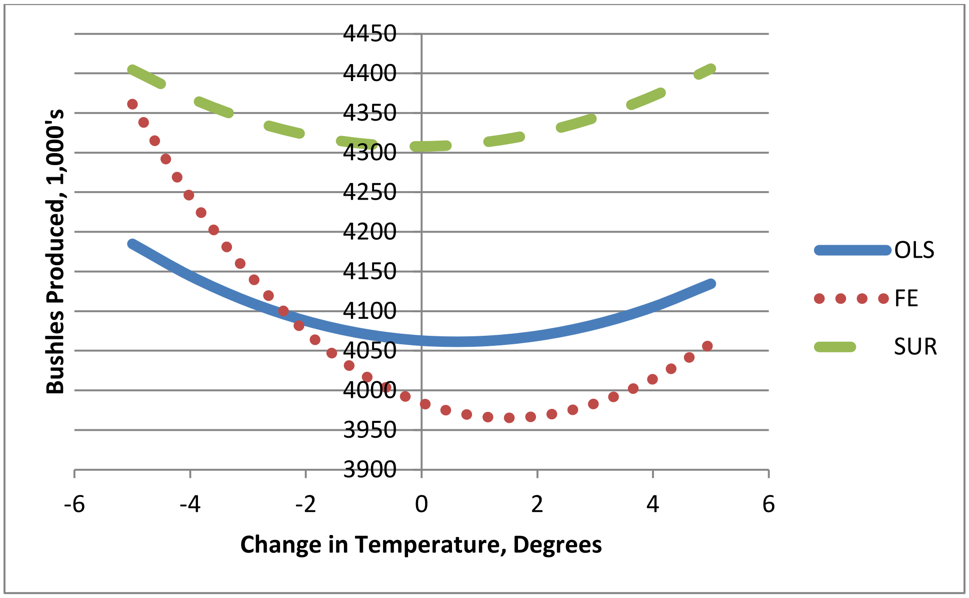
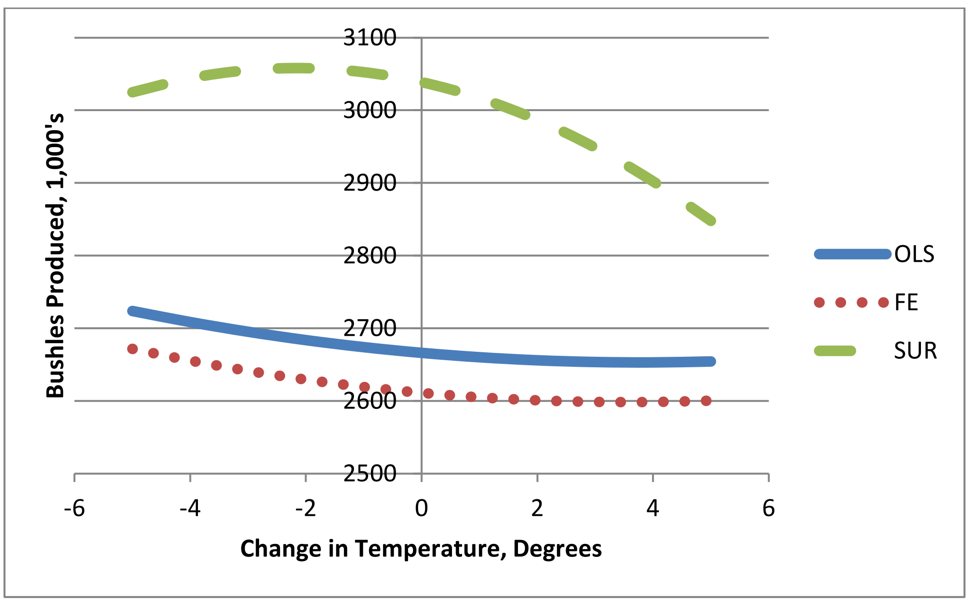


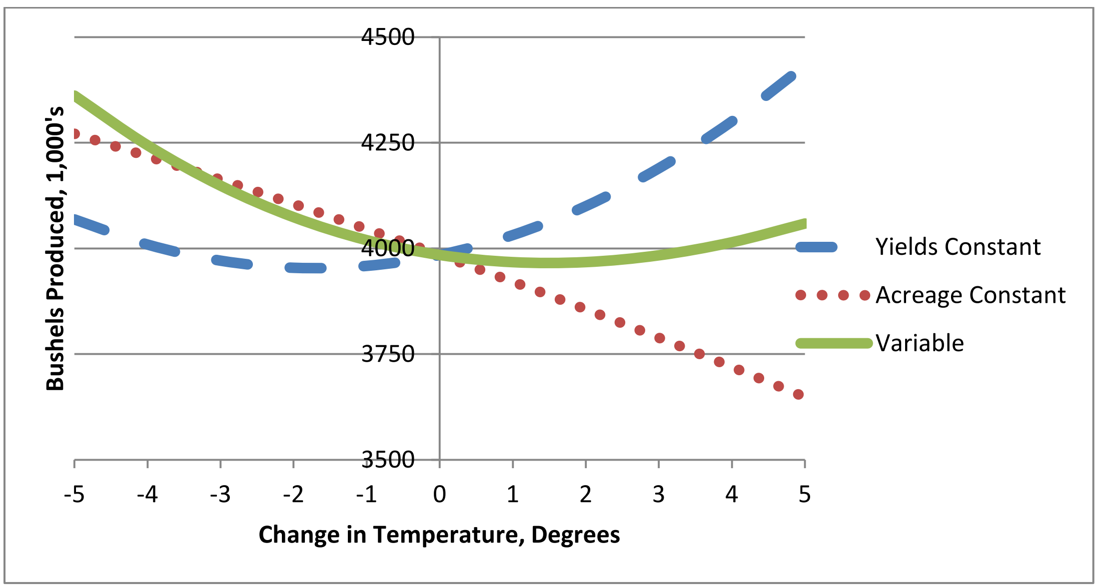
Figure 5.10. Estimated Average County Sorghum Production with a Change in Climate Temperatures



The results of the simulations for the impact of temperature changes on total production are highly dependent on the specific crops analyzed. The variations in temperature away from the mean for wheat production is expected to positively impact total bushels produced, while corn and sorghum may be negatively impacted.

Given the distinct quadratic relationship of wheat supply and climate change, figure 5.11 graphically shows the impact of climate change if acreage and yield responses were individually estimated to predict grain supply. By holding acreage constant, which traditional yield response models estimate, the impact of climate change on total supply is strictly negative. However holding yields constant, increases in acres planted significantly impact total supply. The two distinct differences in total supply estimates for acreage and yield response to climate change indicate a need for a more complete supply estimate which incorporates both supply responses.

Figure 5.11. Total Supply Holding Yield and Acreage Constant[37]



[37] The estimates presented are using the wheat fixed effects model. Yields constant implies total supply with acreage estimated and yields held constant given no change in climate temperature. Acreage constant is the converse of the yield constant. Variable is the method presented in the earlier graphs, were both acreage and yield responses are estimated for changes in climate temperatures.

The variable line displays the most accurate total supply estimation as it incorporates both acreage and yield responses. Previous supply methods which did not account for these supply differences are proven inaccurate.

While the result proves the importance of combined yield and acreage response estimates some considerations are in order when interpreting the precision of this analysis. The climate estimates from an increase in temperature should be interpreted as likely being overstated. With an increase in temperature, seasonal yields are expected to decline, as shown in the change in weather results presented earlier, this would decrease total planted acres in the long run. The production changes shown through the changes in the climate temperatures hold expected yields constant however these would be negatively impacted, decreasing the number of acres planted. The impact of technological progress could diminish any negative impact of climate or weather. Furthermore, any policies that may distort the traditional incentives, would impact supply differently and be unquantifiable through these simulations. Additional tables for the changes in temperature and precipitation are attached in Appendix B. Although the precision of the estimates may need slight correction, the requirement of combined acreage and yield response for total supply is proven.

Chapter 6 - Conclusions and Implications

A greater understanding of land use decisions is imperative for the agricultural industry to move forward. Land use decisions impact the environment, commodity markets, and the general economy. With changes in agriculture due to higher and more volatile prices, biofuels, and potential looming changes in climate, understanding how the industry might adjust or adapt to these incredible shifts is valuable. Previous research has distinctly separated land use into acreage and yield responses to prices, ignoring the intricate relationship between the two production decisions. This separation was shown to underestimate the complete impact of commodity supply responses, contradicting earlier research (Menz and Pardey 1983). Understanding the varying impact of weather on the select crops is important with the mounting concern of changes in climate or weather patterns.

With models estimated at the aggregate county level, this study provided insight into the production dynamics of many producers across a larger geographic region. Farm level data are valuable as they provide site specific impacts on individual farmers; however replication of the results to other regions or producers is more limited. Furthermore, many of the variables used in farm level analysis are also aggregated at county levels due to the limited number of weather stations in a particular county.

A negative aspect of aggregated data involves the assumption of homogenous land qualities. To account for the heterogeneity across the state a fixed effects model was used. The SUR model was used to account for contemporaneous causes for changes in the crops across space. While this method provides insight into yearly or seasonal differences, it is limited as it does not account for county level production differences as the fixed effects model quantifies. The ordinary least squares method is valuable for its simplicity of analysis. Although many of the assumptions of OLS models likely do not hold with panel data, it can still remain valuable as many of the assumptions in the other models force or ignore relationships that may reduce the efficiency of the coefficients. The correlation of many of the variables used in this research likely resulted in less efficient coefficients which does not change the sign or value of the variables but merely the statistical significance. Despite the expected correlation of the variables, many were still found to be significant at high confidence levels. The robustness of the variables across the models was also indicative of the true significance of the variables.

The results showed high levels of statistical significance of prices and yield expectations across the four crops in the acreage model. The own-prices and yields, were positive across each model and crop as theory would predict. The cross-prices and cross-expected yields varied significantly across crops. As discussed earlier, this was likely due to the complex relationship between the crops. The numerous roles of soybeans complicated the analysis, as they are used as long run fertilizer substitutes, as well as a competitive crop for acreage when prices change. The impact of lagged acreage was highly significant across all the models and crops. This variable was highly collinear with the climate variables as well as prices and expected yields. However the importance of lagged acreage showed producers persistence or habit for resisting planting of different crops.

The significance of lagged basis prices indicated farmers' perception of futures prices and cash prices at harvest are influenced by past market behavior. With the higher volatility seen in commodity markets, the efficiency of futures prices is likely questioned. If basis prices are showing trends in the efficiency of futures prices, farmers must interpret these forward contracts with complete knowledge. The incorporation of futures and basis prices quantifies producer price expectations, as they are more complete together than separated.

The role of risk and volatility was tested using previous methods (Chavas and Holt 1990; Lin and Dismukes 2007); however the significance of the regression results was limited. Potential future research could analyze the impact of this volatility on producer decisions. Effective evaluations of risk are likely more quantifiable on less aggregate scales. As the role of planting multiple crops or risk hedging is more observable at the individual level. While there is extensive research left in understanding commodity markets and the role of these markets on producer outcomes, this research has presented greater motives for future research on the topic.

The results from the yield response regressions showed a strong impact of prices on yields. Although the ambiguity of the positive price coefficients for yields could be explained by multiple reasons including land quality, unaccounted for input use, as well as potential differences in labor allocation; the impact of prices is a necessary and important variable when analyzing yield and total supply responses. The impact of weather and climate greatly influenced yields. Many of the growing seasons showed decreasing marginal returns to precipitation for the four crops. However, the months before planting showed increasing marginal returns on yields. The impact of temperature was less consistent across the three models. This is likely due to the aggregated temperature variable which does not account for daily variation, as well as nighttime temperatures which thoroughly impact yields. The impact of acreage on yields was positive in the OLS and SUR models due to potential returns to scale. However, when accounting for county differences in the FE model, the concept of marginal acreage was proven. Corn yields were most impacted by encroachment onto inferior quality land. Crops yields were also shown to be increasing over time; only corn yields have not reached their maximum level.

The results presented total supply elasticities which incorporated yield and acreage responses to prices as well as the subsequent impact of marginal acreage on supply. Wheat and sorghum were the most elastic to price changes in the short run. Wheat and corn were the most elastic to prices in the long run. The substantial increase of the corn price elasticities in the long run were due to the largest marginal effect of lagged acreage of the four crops. As discussed earlier this could be due to a variety of reasons including the omission of policy variables in the acreage model.

The climate and weather simulations showed strong potential impacts on total supply for Kansas agriculture. Increases in seasonal temperatures are expected to decrease yields in the short run, thus influencing long run supply. Increases in precipitation would increase all yields except for wheat. The specific impact of climate increases in temperature was model dependent, however when averaged, the impact was negative for corn and sorghum, positive for wheat and soybeans, with a five degree increase in temperature. The full effect of a change in climate on agricultural supply will be influenced by policies and which incentives are given to which specific crops.

This research is important for policy makers as well as agribusinesses which rely on grain commodities for production. By more accurately estimating supply response to prices and climate, firms and governments are more likely to correctly predict production behavior and prices at harvest due to supply decisions. This increased supply knowledge is beneficial for commodity markets in explaining future prices. The results are also indicative for climatologists, for estimating future grain supply with the expected changes in climate and weather patterns. The combination of acreage and yield response was proven vital for more accurate supply estimates when compared to previous methods.

Policy Implications

The impact of government policies will undoubtedly determine many land use decisions. If policies or prices distort full market outcomes, the efficiency of the market could be questioned. Increases in policies supporting biofuel production are changing producer decisions. For this reason the long term corn supply elasticity was shown to increase significantly more than the other crops, compared to the short run elasticity. A policy which favors a specific crop over another will reduce acreage of the other crop.

With the expansion of corn acreage, the results showed aggregate yield measures are decreasing from the increase of marginal acreage used in corn production. In the short run this may decrease total supply of agricultural commodities as select acreage is more suitable to specific crops. In the long run farmers can increase their soil quality through increased input use. With the growing concern of decreasing aquifer water levels and nitrogen leakage in waterways, the environmental concerns of the expanded acreage should be understood more clearly.

Changes in climate and weather will impact commodity supply. Wheat yields were shown to be negatively impacted by higher seasonal temperatures. Soybean supply and yields were shown to be the least affected from these changes. If polices are designed for set production quotas, acreage/prices must adjust as yields and acreage change. With soybeans least impacted by changes in weather, policies which increase the acreage of other crops through reductions in soybean acreage would be more disastrous if changes in climate were to occur. To maintain yield levels farmers must also increase input use which would have a negative impact on local environments.

The impact of policies geared at reducing the price volatility of commodity prices would profoundly impact production decisions. The reduction of risk would show the true value of prices on production decisions. The economic impacts of risk reduction on the market as a whole are beyond this research. However, this reduction in risk would change production in a variety of ways. Farmers would be more likely to reduce crop diversification as hedging through multiple crops would no longer be necessary. With the reduction of volatility, farmers would also be more likely to apply expensive inputs when output prices are known. Exact knowledge of these impacts are yet unknown.

Further Research

Further research could advance these results in multiple directions. As discussed earlier, further research in farmer price expectations and the role of the futures market. The research here has proven the significance of futures and basis pricing, however by extending that to include how risk in these markets impacts decisions could prove important. If policymakers do decide policies which aim at lowering the volatility in these markets, how will these changes shift the market and land use?

Analyzing farm level data has been discussed throughout this paper for its benefits and shortcomings. Extending this research to the individual level, however, could provide insight into the role of pricing in crop rotations and double cropping. Furthermore research analyzing site specific conditions which incorporate advanced agronomic measures coupled with economic conditions would provide more accurate yield response to prices and weather. Measures of soil quality would also prove to be important when analyzing non-homogenous land. While there are limitations with each method of analysis, combining the research to create a greater knowledge of land use will allow for a more efficient and less volatile market.

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Appendix A - Summary Statistics

Table A.0.1. Summary Statistics, Corn OLS and FE Acreage Models

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	2784	22.84	24.71	0.20	164.50
PX	2784	4.00	0.43	3.09	5.12
SUB1	2784	5.25	0.53	4.49	6.25
SUB2	2784	9.44	1.22	7.11	13.57
PF	2784	405.17	128.81	248.94	761.46
LA	2784	22.15	24.10	0.20	142.80
EYC	2784	104.57	31.91	44.60	193.20
EYSoy	2784	30.28	8.02	13.14	56.40
EYSorgh	2784	63.25	11.75	34.00	101.40
EYW	2784	35.38	5.54	21.60	59.20
BPX	2784	-0.34	0.38	-1.13	0.67
BPS1	2784	-0.70	0.66	-1.98	0.61
BPS2	2784	-0.68	0.68	-1.74	1.21
CP	2784	28.64	7.27	13.62	45.40
CT	2784	59.56	1.78	54.44	63.52
CP2	2784	873.13	416.39	185.59	2060.71
CT2	2784	3550.50	211.24	2963.93	4034.16

Table A.0.2. Summary Statistics, Soybeans OLS and FE Acreage Models

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	2764	23.69	24.41	0.05	126.50
PX	2764	9.43	1.19	7.11	13.57
SUB1	2764	5.25	0.53	4.49	6.25
SUB2	2764	4.00	0.43	3.09	5.12
PF	2764	403.97	127.94	248.94	761.46
LA	2764	23.13	24.25	0.05	126.50
EYC	2764	104.21	31.89	44.60	193.20
EYSoy	2764	30.20	8.01	13.14	56.40
EYSorgh	2764	63.33	11.69	34.60	101.40
EYW	2764	35.38	5.56	21.60	59.20
BPX	2764	-0.68	0.68	-1.74	1.21
BPS1	2764	-0.70	0.66	-1.98	0.61
BPS2	2764	-0.33	0.38	-1.13	0.67
CP	2764	27.73	6.87	13.35	42.39
CT	2764	62.34	1.79	57.09	66.27
CP2	2764	816.44	379.07	178.20	1797.17
CT2	2764	3888.85	221.51	3259.40	4392.32

Table A.0.3. Summary Statistics, Sorghum OLS and FE Acreage Models

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	2796	37.36	26.15	0.30	199.00
PX	2796	3.50	0.43	2.60	4.62
SUB1	2796	5.25	0.53	4.49	6.25
SUB2	2796	9.43	1.22	7.11	13.57
PF	2796	404.70	128.72	248.94	761.46
LA	2796	37.86	26.38	0.90	199.00
EYC	2796	104.46	31.94	44.60	193.20
EYSoy	2796	30.25	8.02	13.14	56.40
EYSorgh	2796	63.15	11.77	34.00	101.40
EYW	2796	35.35	5.52	21.60	58.40
BPX	2796	-0.33	0.41	-1.30	0.64
BPS1	2796	-0.70	0.66	-1.98	0.61
BPS2	2796	-0.68	0.68	-1.74	1.21
CP	2796	27.61	6.89	13.35	42.39
CT	2796	62.34	1.79	57.09	66.27
CP2	2796	809.86	379.75	178.20	1797.17
CT2	2796	3888.92	221.47	3259.40	4392.32

Table A.0.4. Summary Statistics, Wheat OLS and FE Acreage Models

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	2732	106.00	79.72	1.10	525.00
PX	2732	5.29	0.70	3.98	6.65
SUB1	2732	3.71	0.60	2.49	5.37
SUB2	2732	9.25	1.49	5.48	12.91
PF	2732	382.24	115.73	238.75	673.47
LA	2732	106.85	80.11	3.40	525.00
EYC	2732	104.19	31.86	44.60	193.20
EYSoy	2732	30.17	7.96	13.14	56.40
EYSorgh	2732	63.15	11.81	34.00	101.40
EYW	2732	35.49	5.65	21.60	62.20
BPX1	2732	-0.71	0.67	-1.98	0.61
BSUB1	2732	-0.34	0.39	-1.13	0.67
BSUB2	2732	-0.65	0.67	-1.65	1.21
CP	2732	34.23	8.57	15.98	54.90
CT	2732	56.75	1.71	51.89	60.61
CP2	2732	1245.39	589.82	255.42	3014.23
CT2	2732	3223.20	193.35	2692.65	3673.20

Table A.0.5. Summary Statistics, Corn SUR Acreage Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	1581	22.49	22.31	1.00	135.60
PX	1581	4.02	0.43	3.09	5.12
SUB1	1581	5.24	0.53	4.49	6.25
SUB2	1581	9.52	1.22	7.11	13.57
PF	1581	409.31	132.53	248.94	761.46
LA	1581	22.01	22.25	1.00	135.60
EYC	1581	102.17	32.19	46.60	193.20
EYSoy	1581	29.26	8.50	13.14	56.40
EYSorgh	1581	64.97	11.06	35.80	101.40
EYW	1581	35.28	5.85	23.02	56.40
BPX1	1581	-0.37	0.34	-1.13	0.34
BSUB1	1581	-0.72	0.66	-1.98	0.61
BSUB2	1581	-0.71	0.67	-1.74	1.21
CP	1581	30.84	6.29	16.05	45.40
CT	1581	59.57	1.78	54.44	63.52
CP2	1581	990.57	379.09	257.70	2060.71
CT2	1581	3551.80	211.11	2963.93	4034.16

Table A.0.6. Summary Statistics, Soybean SUR Acreage Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	1581	32.33	24.72	0.45	126.50
PX	1581	9.52	1.22	7.11	13.57
SUB1	1581	5.24	0.53	4.49	6.25
SUB2	1581	4.02	0.43	3.09	5.12
PF	1581	409.31	132.53	248.94	761.46
LA	1581	22.01	22.25	1.00	135.60
EYC	1581	102.17	32.19	46.60	193.20
EYSoy	1581	29.26	8.50	13.14	56.40
EYSorgh	1581	64.97	11.06	35.80	101.40
EYW	1581	35.28	5.85	23.02	56.40
BPX1	1581	-0.71	0.67	-1.74	1.21
BSUB1	1581	-0.72	0.66	-1.98	0.61
BSUB2	1581	-0.37	0.34	-1.13	0.34
CP	1581	29.73	5.95	15.65	42.39
CT	1581	62.37	1.79	57.09	66.12
CP2	1581	918.96	343.58	244.86	1797.17
CT2	1581	3892.78	222.57	3259.40	4372.15

Table A.0.7. Summary Statistics, Sorghum SUR Acreage Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	1581	39.92	26.57	0.90	155.30
PX	1581	3.52	0.42	2.60	4.59
SUB1	1581	5.24	0.53	4.49	6.25
SUB2	1581	9.52	1.22	7.11	13.57
PF	1581	409.31	132.53	248.94	761.46
LA	1581	40.66	26.57	1.10	155.30
EYC	1581	102.17	32.19	46.60	193.20
EYSoy	1581	29.26	8.50	13.14	56.40
EYSorgh	1581	64.97	11.06	35.80	101.40
EYW	1581	35.28	5.85	23.02	56.40
BPX1	1581	-0.38	0.38	-1.30	0.56
BSUB1	1581	-0.72	0.66	-1.98	0.61
BSUB2	1581	-0.71	0.67	-1.74	1.21
CP	1581	29.73	5.95	15.65	42.39
CT	1581	62.37	1.79	57.09	66.12
CP2	1581	918.96	343.58	244.86	1797.17
CT2	1581	3892.78	222.57	3259.40	4372.15

Table A.0.8. Summary Statistics, Wheat SUR Acreage Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
A	1581	101.95	90.46	3.70	525.00
PX	1581	5.30	0.71	3.98	6.65
SUB1	1581	3.72	0.62	2.49	5.37
SUB2	1581	9.25	1.51	5.48	12.91
PF	1581	381.28	116.31	238.75	673.47
LA	1581	102.69	90.93	3.70	525.00
EYC	1581	100.90	32.06	46.60	193.20
EYSoy	1581	28.94	8.36	13.14	56.40
EYSorgh	1581	64.51	11.23	35.80	101.40
EYW	1581	35.28	5.85	23.02	56.40
BPX1	1581	-0.72	0.66	-1.98	0.61
BSUB1	1581	-0.34	0.39	-1.13	0.67
BSUB2	1581	-0.64	0.68	-1.65	1.21
CP	1581	36.76	7.52	18.80	54.90
CT	1581	57.05	1.42	52.73	60.25
CP2	1581	1407.51	543.96	353.59	3014.23
CT2	1581	3256.55	160.99	2780.62	3630.09

Table A.0.9. Summary Statistics, Corn OLS and FE Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	2784	108.18	36.73	18.00	207.00
T	2784	17.95	8.80	2.00	33.00
T2	2784	399.71	317.76	4.00	1089.00
PF	2784	405.17	128.81	248.94	761.46
PX	2784	4.00	0.43	3.09	5.12
A	2784	22.84	24.71	0.20	164.50
A%	2784	12.37	10.73	0.10	59.36
CT1	2784	39.24	2.25	32.43	45.22
CT2	2784	59.22	2.04	53.23	63.61
CT3	2784	76.87	1.51	71.98	81.14
CT4	2784	56.02	1.99	50.25	60.64
CP1	2784	3.27	1.10	0.92	6.99
CP2	2784	7.11	1.71	2.73	12.76
CP3	2784	11.15	2.29	4.79	16.48
CP4	2784	7.11	2.95	1.88	14.56
WP1	2784	0.02	1.95	-6.22	9.17
WP2	2784	0.01	3.04	-7.70	15.27
WP3	2784	0.23	4.81	-12.67	23.59
WP4	2784	-0.37	3.59	-12.75	20.30
WT1	2784	-0.16	3.68	-12.01	8.48
WT2	2784	0.02	2.66	-10.29	6.00
WT3	2784	0.13	2.06	-6.85	7.15
WT4	2784	0.19	2.07	-6.79	6.04
$WP1^2$	2784	3.80	6.20	0.00	84.16
$WP2^2$	2784	9.26	15.77	0.00	233.11
$WP3^2$	2784	23.18	37.58	0.00	556.25
$WP4^2$	2784	13.04	30.90	0.00	412.13
$WT1^2$	2784	13.52	16.24	0.00	144.13
$WT2^2$	2784	7.04	9.64	0.00	105.84
$WT3^2$	2784	4.26	7.12	0.00	51.17
$WT4^2$	2784	4.31	5.81	0.00	46.15

Table A.0.10. Summary Statistics, Corn SUR Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	1581	107.24	36.33	21.00	206.00
T	1581	16.00	8.95	1.00	31.00
T2	1581	336.00	295.09	1.00	961.00
PF	1581	409.31	132.53	248.94	761.46
PX	1581	4.02	0.43	3.09	5.12
A	1581	22.49	22.31	1.00	135.60
A%	1581	12.40	9.68	0.20	50.45
CT1	1581	39.19	2.21	32.96	45.22
CT2	1581	59.24	2.03	53.23	63.59
CT3	1581	76.90	1.53	72.35	81.04
CT4	1581	56.05	2.00	50.38	60.64
CP1	1581	3.62	0.99	1.15	6.99
CP2	1581	7.57	1.53	3.50	12.76
CP3	1581	11.75	2.02	5.36	16.48
CP4	1581	7.89	2.62	2.39	14.56
WP1	1581	0.06	2.06	-6.22	7.62
WP2	1581	0.02	3.19	-7.70	15.27
WP3	1581	0.38	4.94	-12.67	22.09
WP4	1581	-0.43	3.77	-12.75	18.82
WT1	1581	-0.12	3.45	-12.01	7.83
WT2	1581	-0.18	2.64	-9.89	5.88
WT3	1581	0.20	2.06	-6.85	7.08
WT4	1581	0.25	2.03	-6.79	5.96
$WP1^2$	1581	4.23	6.24	0.00	58.02
$WP2^2$	1581	10.16	17.35	0.00	233.11
$WP3^2$	1581	24.52	38.90	0.00	488.14
$WP4^2$	1581	14.40	32.12	0.00	354.34
$WT1^2$	1581	11.90	14.67	0.00	144.13
$WT2^2$	1581	6.98	10.40	0.00	97.71
$WT3^2$	1581	4.27	7.66	0.00	50.08
$WT4^2$	1581	4.18	6.20	0.00	46.15

Table A.0.11. Summary Statistics, Soybeans OLS and FE Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	2764	31.09	10.86	6.90	61.00
T	2764	17.92	8.77	2.00	33.00
T2	2764	398.02	317.12	4.00	1089.00
PF	2764	403.97	127.94	248.94	761.46
PX	2764	9.43	1.19	7.11	13.57
A	2764	23.69	24.41	0.05	126.50
A%	2764	17.69	18.76	0.02	72.22
CT1	2764	49.19	2.23	43.01	54.62
CT2	2764	68.87	1.63	63.49	72.73
CT3	2764	78.42	1.62	73.27	83.22
CT4	2764	56.02	1.99	50.25	60.64
CP1	2764	5.05	1.45	1.66	9.26
CP2	2764	8.56	1.90	4.04	13.59
CP3	2764	6.98	1.54	2.97	11.43
CP4	2764	7.14	2.94	1.88	14.56
WP1	2764	0.00	2.33	-7.46	10.94
WP2	2764	0.11	3.95	-9.43	17.98
WP3	2764	0.11	3.79	-8.59	20.58
WP4	2764	-0.38	3.61	-12.75	20.30
WT1	2764	-0.02	2.94	-8.27	6.49
WT2	2764	0.02	2.30	-8.83	6.30
WT3	2764	0.25	2.45	-7.14	8.48
WT4	2764	0.19	2.07	-6.79	6.04
$WP1^2$	2764	5.43	8.68	0.00	119.66
$WP2^2$	2764	15.60	26.44	0.00	323.32
$WP3^2$	2764	14.38	26.94	0.00	423.45
$WP4^2$	2764	13.14	31.01	0.00	412.13
$WT1^2$	2764	8.63	9.28	0.00	68.34
$WT2^2$	2764	5.30	7.27	0.00	77.97
$WT3^2$	2764	6.05	9.18	0.00	72.00
$WT4^2$	2764	4.30	5.82	0.00	46.15

Table A.0.12. Summary Statistics, Soybeans SUR Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	1581	30.68	11.03	6.90	61.00
T	1581	16.00	8.95	1.00	31.00
T2	1581	336.00	295.09	1.00	961.00
PF	1581	409.31	132.53	248.94	761.46
PX	1581	9.52	1.22	7.11	13.57
A	1581	32.33	24.72	0.45	126.50
A%	1581	23.12	18.90	0.11	72.05
CT1	1581	49.23	2.24	43.01	54.62
CT2	1581	68.90	1.62	63.49	72.73
CT3	1581	78.46	1.65	73.43	83.06
CT4	1581	56.05	2.00	50.38	60.64
CP1	1581	5.49	1.25	1.74	9.26
CP2	1581	9.08	1.67	4.97	13.59
CP3	1581	7.26	1.44	3.06	11.43
CP4	1581	7.89	2.62	2.39	14.56
WP1	1581	-0.07	2.41	-7.46	10.94
WP2	1581	0.33	4.22	-9.32	17.98
WP3	1581	0.16	3.86	-8.10	18.79
WP4	1581	-0.43	3.77	-12.75	18.82
WT1	1581	-0.37	2.90	-7.66	6.21
WT2	1581	0.03	2.43	-8.83	6.22
WT3	1581	0.40	2.47	-7.14	8.48
WT4	1581	0.25	2.03	-6.79	5.96
$WP1^2$	1581	5.78	9.26	0.00	119.66
$WP2^2$	1581	17.87	29.70	0.00	323.32
$WP3^2$	1581	14.90	26.80	0.00	352.88
$WP4^2$	1581	14.40	32.12	0.00	354.34
$WT1^2$	1581	8.55	9.17	0.00	58.68
$WT2^2$	1581	5.89	8.04	0.00	77.97
$WT3^2$	1581	6.26	9.67	0.00	72.00
$WT4^2$	1581	4.18	6.20	0.00	46.15

Table A.0.13. Summary Statistics, Sorghum OLS and FE Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	2796	64.84	18.21	12.00	134.00
T	2796	17.90	8.80	2.00	33.00
T2	2796	397.70	317.39	4.00	1089.00
PF	2796	404.70	128.72	248.94	761.46
PX	2796	3.50	0.43	2.60	4.62
A	2796	37.36	26.15	0.30	199.00
A%	2796	19.67	9.84	0.20	63.04
CT1	2796	49.19	2.24	43.01	54.62
CT2	2796	68.87	1.63	63.49	72.73
CT3	2796	78.42	1.61	73.27	83.22
CT4	2796	56.02	1.99	50.25	60.64
CP1	2796	5.02	1.46	1.66	9.26
CP2	2796	8.52	1.91	4.04	13.59
CP3	2796	6.97	1.54	2.97	11.43
CP4	2796	7.10	2.94	1.88	14.56
WP1	2796	-0.01	2.32	-7.46	10.94
WP2	2796	0.12	3.94	-9.43	17.98
WP3	2796	0.09	3.78	-8.59	20.58
WP4	2796	-0.38	3.59	-12.75	20.30
WT1	2796	-0.02	2.94	-8.27	6.49
WT2	2796	0.02	2.30	-8.83	6.30
WT3	2796	0.24	2.45	-7.14	8.48
WT4	2796	0.19	2.06	-6.79	6.04
$WP1^2$	2796	5.40	8.65	0.00	119.66
$WP2^2$	2796	15.54	26.47	0.00	323.32
$WP3^2$	2796	14.27	26.81	0.00	423.45
$WP4^2$	2796	13.05	30.84	0.00	412.13
$WT1^2$	2796	8.66	9.32	0.00	68.34
$WT2^2$	2796	5.30	7.25	0.00	77.97
$WT3^2$	2796	6.03	9.16	0.00	72.00
$WT4^2$	2796	4.30	5.82	0.00	46.15

Table A.0.14. Summary Statistics, Sorghum SUR Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	1581	67.52	17.45	17.00	130.00
T	1581	16.00	8.95	1.00	31.00
T2	1581	336.00	295.09	1.00	961.00
PF	1581	409.31	132.53	248.94	761.46
PX	1581	3.52	0.42	2.60	4.59
A	1581	39.92	26.57	0.90	155.30
A%	1581	20.32	9.42	0.69	63.04
CT1	1581	49.23	2.24	43.01	54.62
CT2	1581	68.90	1.62	63.49	72.73
CT3	1581	78.46	1.65	73.43	83.06
CT4	1581	56.05	2.00	50.38	60.64
CP1	1581	5.49	1.25	1.74	9.26
CP2	1581	9.08	1.67	4.97	13.59
CP3	1581	7.26	1.44	3.06	11.43
CP4	1581	7.89	2.62	2.39	14.56
WP1	1581	-0.07	2.41	-7.46	10.94
WP2	1581	0.33	4.22	-9.32	17.98
WP3	1581	0.16	3.86	-8.10	18.79
WP4	1581	-0.43	3.77	-12.75	18.82
WT1	1581	-0.37	2.90	-7.66	6.21
WT2	1581	0.03	2.43	-8.83	6.22
WT3	1581	0.40	2.47	-7.14	8.48
WT4	1581	0.25	2.03	-6.79	5.96
$WP1^2$	1581	5.78	9.26	0.00	119.66
$WP2^2$	1581	17.87	29.70	0.00	323.32
$WP3^2$	1581	14.90	26.80	0.00	352.88
$WP4^2$	1581	14.40	32.12	0.00	354.34
$WT1^2$	1581	8.55	9.17	0.00	58.68
$WT2^2$	1581	5.89	8.04	0.00	77.97
$WT3^2$	1581	6.26	9.67	0.00	72.00
$WT4^2$	1581	4.18	6.20	0.00	46.15

Table A.0.15. Summary Statistics, Wheat OLS and FE Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	2732	35.88	9.67	9.00	80.00
T	2732	18.53	8.58	3.00	33.00
T2	2732	417.02	318.34	9.00	1089.00
PF	2732	382.24	115.73	238.75	673.47
PX	2732	5.29	0.70	3.98	6.65
A	2732	106.00	79.72	1.10	525.00
A%	2732	50.39	22.59	0.74	97.92
CT1	2732	78.43	1.61	73.27	83.17
CT2	2732	62.82	1.83	56.65	67.60
CT3	2732	34.83	2.18	28.16	40.34
CT4	2732	54.24	2.06	47.88	59.03
CT5	2732	76.60	1.47	71.71	80.88
CP1	2732	6.97	1.55	2.97	11.43
CP2	2732	5.35	2.20	1.43	11.20
CP3	2732	4.68	2.06	1.16	11.76
CP4	2732	9.40	2.30	3.95	15.70
CP5	2732	7.83	1.75	3.31	13.40
WP1	2732	0.12	3.81	-8.59	20.58
WP2	2732	-0.23	3.17	-8.79	19.75
WP3	2732	-0.12	2.38	-7.71	12.35
WP4	2732	-0.09	3.31	-9.08	16.70
WP5	2732	0.20	4.00	-10.80	19.30
WT1	2732	0.13	2.50	-6.71	8.48
WT2	2732	-0.01	2.15	-6.74	6.32
WT3	2732	0.17	3.01	-9.96	6.39
WT4	2732	0.17	2.50	-8.53	5.91
WT5	2732	0.04	2.21	-6.36	7.84
$WP1^2$	2732	14.55	27.06	0.00	423.45
$WP2^2$	2732	10.12	25.29	0.00	390.18
$WP3^2$	2732	5.70	10.41	0.00	152.57
$WP4^2$	2732	10.93	18.50	0.00	278.82
$WP5^2$	2732	16.01	30.68	0.00	372.49
$WT1^2$	2732	6.28	9.21	0.00	72.00
$WT2^2$	2732	4.61	5.84	0.00	45.36
$WT3^2$	2732	9.10	11.68	0.00	99.15
$WT4^2$	2732	6.27	7.48	0.00	72.76
$WT5^2$	2732	4.90	7.48	0.00	61.47

Table A.0.16. Summary Statistics, Wheat SUR Yield Model

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Y	1581	35.86882	9.744669	9	71
T	1581	16	8.947102	1	31
T2	1581	336	295.0916	1	961
PF	1581	381.2803	116.305	238.7505	673.4748
PX	1581	5.304581	0.711019	3.981	6.652
A	1581	101.9462	90.46344	3.7	525
A%	1581	44.16097	20.49477	4.78	95.02
CT1	1581	78.66442	1.349655	75.2	82.0918
CT2	1581	63.19347	1.419601	58.7	66.395
CT3	1581	35.03202	2.09987	28.15625	40.3425
CT4	1581	54.70667	1.60505	49.60333	59.03
CT5	1581	76.83388	1.187667	73.665	79.945
CP1	1581	7.257649	1.437455	3.056	11.428
CP2	1581	5.959567	1.947079	1.651	11.143
CP3	1581	5.234564	1.966421	1.553	11.755
CP4	1581	10.07814	1.972672	4.664	15.699
CP5	1581	8.225122	1.607695	3.823	13.3975
WP1	1581	0.0946616	3.916138	-8.1	18.79
WP2	1581	-0.3798862	3.319483	-8.79	18.12
WP3	1581	-0.120797	2.559655	-7.71	12.35
WP4	1581	0.0323719	3.424938	-9.08	16.7
WP5	1581	0.2491588	4.210234	-10.8	19.3
WT1	1581	0.173074	2.531823	-6.48	8.48
WT2	1581	0.069475	2.159801	-6.44	6.32
WT3	1581	0.1383112	3.03768	-9.2	6.39
WT4	1581	0.1729159	2.556134	-7.6	5.91
WT5	1581	0.0376787	2.185897	-5.94	7.84
$WP1^2$	1581	15.33336	26.82956	0	352.88
$WP2^2$	1581	11.15385	25.55873	0	328.15
$WP3^2$	1581	6.56043	11.43995	0	152.57
$WP4^2$	1581	11.72156	20.31351	0	278.82
$WP5^2$	1581	17.77399	32.99997	0	372.49
$WT1^2$	1581	6.434151	9.633386	0	71.995
$WT2^2$	1581	4.664311	6.00207	0	41.474
$WT3^2$	1581	9.238583	11.42062	0	84.686
$WT4^2$	1581	6.559249	7.365809	0	57.775
$WT5^2$	1581	4.774201	7.479015	0	61.466

Appendix B - Fixed Effects County Constant Results

Presented below are the Fixed Effects results for the constant county terms from the models presented earlier. With the results shown earlier in the results section, the constant term is averaged across all of the counties estimated. Fixed effects models can also be shown by expanding the results and presenting the within-group constant estimators, or county specific dummy variables. These county estimators quantify the heterogeneity within the sample. The other econometric models estimated in this research assume homogeneity within the sample. As expected, however, counties vary significantly due to the varying size of agricultural production with the county as well as site specific variables such as land quality and level of irrigation. This result shows the need to account for the heterogeneity within the sample. More accurate field level data which quantifies the heterogeneity of production across the state would be less likely to require fixed effects models. However due to the aggregation of the sample presented here, quantifying the differences across the cross-sectional units provides important results for this analysis. The results are presented below in tables B.1-B.2, with county Allen as the omitted county due to collinearity.

The results show the largest differences in acreage planted between counties are in the wheat model. The largest difference is between Sumner and Chautauqua counties, differing by 164 thousand wheat acres planted. With the close proximity of these counties, this result is most likely due to differences in county size which is ignored in the SUR and OLS models. In the yield model, corn shows the largest difference in county values. This result is expected due to corn producing the highest yield per acre as well as the most likely to be produced with irrigation. With irrigation significantly impacting yields, quantifying the county heterogeneity due to irrigation is important for analysis. Gray and Russell counties present the largest difference in corn yields through the constant terms, differing by 106 bushels per acre. This result follows the observed values as well; as the county average yields over the analysis differed by 105 bushels per acre. Yield differences this large can only be explained by significant differences in irrigation levels between the two counties (Kansas State University Agricultural Experiment Station and Cooperative Extension Service, Corn Production Handbook 2007). The results of the fixed models show the superiority of econometric model in this research versus OLS and SUR, for quantifying the heterogeneity of the sample.

Table B.0.17. Fixed Effects Acreage Response County Constant Terms

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Constant	887.974	1.98	0.05	45.013	0.47	0.64	70.878	0.82	0.42	61.756	0.42	0.67
Anderson	0.099	0.04	0.97	1.397	1.97	0.05	2.515	1.17	0.24	0.652	0.65	0.51
Atchison	-2.770	-1.15	0.25	2.100	1.95	0.05	-2.680	-1.68	0.09	0.171	0.13	0.90
Barber	46.080	9.69	0.00	-3.611	-2.94	0.00	-11.281	-5.32	0.00	0.985	0.50	0.62
Barton	66.843	12.71	0.00	-1.535	-1.12	0.26	-10.321	-4.86	0.00	12.517	4.93	0.00
Bourbon	-8.524	-4.35	0.00	-0.503	-0.87	0.38	-6.060	-3.30	0.00	-2.647	-2.78	0.01
Brown	4.314	1.66	0.10	4.700	2.19	0.03	5.572	2.96	0.00	2.701	1.73	0.08
Butler	16.706	6.32	0.00	1.938	2.05	0.04	-5.075	-2.77	0.01	10.803	5.10	0.00
Chase	-4.880	-2.18	0.03	-0.212	-0.34	0.73	-9.593	-5.35	0.00	-3.608	-3.55	0.00
Chautauqua	-11.254	-6.04	0.00	-0.320	-0.57	0.57	-10.980	-5.99	0.00	-4.790	-5.09	0.00
Cherokee	14.597	4.02	0.00	0.975	1.51	0.13	7.456	3.10	0.00	0.722	0.73	0.47
Cheyenne	41.777	7.56	0.00	-0.350	-0.15	0.88	-14.653	-5.74	0.00	2.619	0.74	0.46
Clark	28.454	2.69	0.01	-3.290	-1.88	0.06	-12.653	-5.51	0.00	-0.064	-0.02	0.98
Clay	31.010	9.77	0.00	-1.290	-1.45	0.15	-3.709	-1.87	0.06	10.438	5.62	0.00
Cloud	44.769	10.98	0.00	-1.104	-1.36	0.18	-8.071	-4.05	0.00	11.748	5.72	0.00
Coffey	2.447	0.97	0.33	0.795	1.23	0.22	3.168	1.68	0.09	1.256	1.00	0.32
Comanche	22.135	5.92	0.00	-4.209	-2.98	0.00	-11.128	-5.10	0.00	2.329	1.09	0.28
Cowley	29.981	8.98	0.00	-0.200	-0.35	0.73	-8.048	-4.38	0.00	5.067	2.97	0.00
Crawford	0.477	0.18	0.86	0.786	0.94	0.35	1.152	0.57	0.57	2.166	1.94	0.05
Decatur	33.884	7.42	0.00	4.980	2.57	0.01	-13.936	-5.91	0.00	2.171	0.76	0.45
Dickinson	53.157	12.91	0.00	0.457	0.58	0.56	-5.735	-2.91	0.00	10.043	4.80	0.00
Doniphan	-1.081	-0.41	0.69	2.288	1.49	0.14	-0.579	-0.32	0.75	-3.381	-2.81	0.01
Douglas	-4.718	-2.34	0.02	0.044	0.06	0.96	-6.262	-3.29	0.00	-1.183	-1.12	0.26
Edwards	37.947	9.41	0.00	0.481	0.26	0.80	-9.057	-4.20	0.00	5.700	2.42	0.02
Elk	-9.169	-4.49	0.00	-0.505	-0.82	0.41	-9.863	-5.53	0.00	-5.124	-4.78	0.00
Ellis	27.676	5.88	0.00	-0.913	-0.62	0.54	-11.756	-4.96	0.00	3.544	1.36	0.18
Ellsworth	28.344	8.25	0.00	-0.624	-0.75	0.45	-11.669	-5.55	0.00	2.758	1.63	0.10

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Finney	70.774	10.86	0.00	2.088	0.69	0.49	-13.519	-5.42	0.00	17.757	4.41	0.00
Ford	73.348	12.25	0.00	-0.860	-0.42	0.68	-13.472	-5.66	0.00	15.277	4.44	0.00
Franklin	-3.830	-1.73	0.08	0.674	0.96	0.34	0.379	0.20	0.84	-0.720	-0.77	0.44
Geary	-0.468	-0.17	0.86	-0.971	-1.32	0.19	-11.026	-5.57	0.00	-1.185	-0.99	0.32
Gove	40.669	8.26	0.00	1.572	0.72	0.47	-13.499	-5.71	0.00	11.960	2.85	0.00
Graham	32.975	6.65	0.00	-1.607	-0.88	0.38	-12.434	-5.34	0.00	6.945	2.05	0.04
Grant	23.249	4.67	0.00	-0.638	-0.23	0.82	-14.022	-5.31	0.00	16.990	3.71	0.00
Gray	57.337	10.61	0.00	1.034	0.42	0.68	-13.228	-5.52	0.00	15.471	4.24	0.00
Greeley	53.750	9.03	0.00	-0.461	-0.19	0.85	-13.616	-5.41	0.00	11.584	1.58	0.11
Greenwood	-6.311	-3.07	0.00	-0.290	-0.52	0.60	-8.104	-4.54	0.00	-3.385	-3.57	0.00
Hamilton	41.918	7.41	0.00	-4.716	-1.72	0.09	-14.312	-5.63	0.00	15.176	1.36	0.17
Harper	90.938	11.71	0.00	-1.981	-1.84	0.07	-10.922	-5.28	0.00	0.010	0.01	1.00
Harvey	39.117	11.56	0.00	-0.553	-0.62	0.53	-5.965	-3.02	0.00	16.476	7.15	0.00
Haskell	34.011	6.98	0.00	2.424	0.66	0.51	-14.466	-5.61	0.00	11.474	2.93	0.00
Hodgeman	37.965	8.68	0.00	-2.530	-1.49	0.14	-13.194	-5.56	0.00	6.750	2.26	0.02
Jackson	-1.128	-0.46	0.65	0.591	0.77	0.44	-6.504	-3.81	0.00	-0.481	-0.37	0.71
Jefferson	-3.762	-1.59	0.11	0.925	0.84	0.40	-5.132	-3.06	0.00	-0.329	-0.29	0.77
Jewell	42.971	9.38	0.00	-1.083	-0.99	0.32	-9.109	-4.12	0.00	16.875	6.58	0.00
Johnson	-6.018	-2.71	0.01	-0.402	-0.56	0.58	-8.174	-4.35	0.00	-3.597	-3.65	0.00
Kearny	38.052	7.77	0.00	-1.184	-0.49	0.62	-14.037	-5.65	0.00	8.616	2.04	0.04
Kingman	76.447	12.94	0.00	-3.132	-2.76	0.01	-10.185	-4.97	0.00	3.804	2.15	0.03
Kiowa	30.372	7.59	0.00	-2.537	-1.71	0.09	-11.261	-5.16	0.00	4.066	1.73	0.08
Labette	10.720	3.44	0.00	0.617	1.07	0.28	-0.979	-0.41	0.68	1.547	1.61	0.11
Lane	37.474	8.14	0.00	-1.847	-1.06	0.29	-13.471	-5.71	0.00	9.207	1.97	0.05
Leavenworth	-5.345	-2.46	0.01	-0.221	-0.29	0.77	-7.982	-4.50	0.00	-1.491	-1.45	0.15
Lincoln	32.231	9.43	0.00	0.243	0.28	0.78	-11.362	-5.41	0.00	3.578	1.96	0.05
Linn	-4.219	-1.99	0.05	-0.388	-0.69	0.49	-3.997	-2.24	0.03	-0.730	-0.74	0.46

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Logan	44.862	8.77	0.00	1.388	0.52	0.60	-14.154	-5.71	0.00	6.622	1.48	0.14
Lyon	1.689	0.66	0.51	0.961	1.41	0.16	-1.364	-0.76	0.45	2.272	1.57	0.12
Marion	45.686	11.48	0.00	1.499	2.07	0.04	-6.775	-3.36	0.00	15.694	5.57	0.00
Marshall	25.742	7.85	0.00	3.021	2.12	0.03	6.240	2.50	0.01	16.187	5.30	0.00
McPherson	83.287	14.59	0.00	-1.637	-1.92	0.06	-6.548	-3.36	0.00	15.684	6.38	0.00
Meade	34.931	8.06	0.00	1.006	0.47	0.64	-14.905	-6.08	0.00	8.994	2.49	0.01
Miami	-4.342	-1.91	0.06	-0.221	-0.32	0.75	-4.771	-2.67	0.01	-1.076	-1.21	0.23
Mitchell	61.480	12.48	0.00	-0.999	-1.05	0.30	-9.637	-4.51	0.00	14.595	6.29	0.00
Montgomery	3.053	1.24	0.21	0.448	0.73	0.47	-5.427	-3.05	0.00	0.694	0.72	0.47
Morris	7.325	2.88	0.00	0.362	0.54	0.59	-7.259	-4.01	0.00	2.419	1.79	0.07
Morton	23.385	4.32	0.00	-2.978	-1.35	0.18	-12.859	-5.27	0.00	14.864	2.67	0.01
Nemaha	6.159	2.16	0.03	3.911	2.72	0.01	-2.081	-1.06	0.29	11.740	4.21	0.00
Neosho	3.095	1.25	0.21	0.111	0.19	0.85	-3.261	-1.87	0.06	0.108	0.10	0.92
Ness	51.180	10.44	0.00	-1.149	-0.74	0.46	-12.340	-5.16	0.00	11.166	2.05	0.04
Norton	31.723	7.14	0.00	4.186	2.09	0.04	-13.096	-5.53	0.00	5.055	1.81	0.07
Osage	-1.378	-0.53	0.59	0.966	1.38	0.17	-0.879	-0.49	0.62	3.777	2.47	0.01
Osborne	42.570	10.12	0.00	-1.871	-1.81	0.07	-11.319	-5.20	0.00	10.831	5.32	0.00
Ottawa	41.437	11.34	0.00	-1.026	-1.25	0.21	-9.475	-4.69	0.00	3.895	2.47	0.01
Pawnee	49.855	10.50	0.00	-1.518	-0.88	0.38	-11.273	-5.03	0.00	10.798	3.65	0.00
Phillips	29.500	7.06	0.00	0.247	0.17	0.86	-11.929	-5.23	0.00	9.928	4.03	0.00
Pottawatomie	0.608	0.25	0.80	-0.004	0.00	1.00	-7.623	-4.15	0.00	2.932	2.18	0.03
Pratt	58.578	12.53	0.00	0.177	0.12	0.90	-9.285	-4.32	0.00	8.310	3.42	0.00
Rawlins	46.002	8.30	0.00	2.277	1.34	0.18	-12.925	-5.55	0.00	6.228	1.77	0.08
Reno	102.796	14.13	0.00	-0.828	-0.81	0.42	-7.344	-3.65	0.00	20.563	6.82	0.00
Republic	32.667	9.16	0.00	1.640	1.05	0.30	-3.619	-1.74	0.08	13.409	5.61	0.00
Rice	55.487	12.84	0.00	-1.217	-1.21	0.23	-8.870	-4.16	0.00	16.306	6.48	0.00
Riley	2.497	0.97	0.33	-0.715	-1.07	0.29	-9.606	-5.13	0.00	2.526	2.27	0.02
Rooks	31.864	7.99	0.00	-0.416	-0.29	0.77	-11.069	-4.88	0.00	9.420	3.57	0.00

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Rush	44.170	9.87	0.00	-2.314	-1.68	0.09	-12.457	-5.48	0.00	8.438	2.96	0.00
Russell	29.732	6.84	0.00	0.213	0.20	0.84	-11.796	-5.19	0.00	3.253	1.71	0.09
Saline	48.184	12.27	0.00	-0.682	-0.84	0.40	-8.822	-4.37	0.00	3.178	2.00	0.05
Scott	47.874	9.66	0.00	0.072	0.03	0.97	-14.538	-5.89	0.00	15.270	3.87	0.00
Sedgwick	81.820	13.28	0.00	-1.160	-1.05	0.29	-6.133	-3.15	0.00	16.658	6.51	0.00
Seward	20.119	5.02	0.00	0.515	0.22	0.82	-13.336	-5.32	0.00	11.254	3.13	0.00
Shawnee	-0.711	-0.27	0.79	-0.269	-0.25	0.80	-6.245	-3.60	0.00	0.464	0.41	0.68
Sheridan	39.307	8.14	0.00	4.838	1.87	0.06	-13.449	-5.47	0.00	8.459	2.38	0.02
Sherman	61.950	9.47	0.00	4.044	1.54	0.12	-13.556	-5.52	0.00	3.049	0.96	0.34
Smith	40.692	9.98	0.00	-0.359	-0.28	0.78	-11.427	-5.03	0.00	15.557	5.98	0.00
Stafford	49.387	11.18	0.00	0.696	0.39	0.70	-9.063	-4.20	0.00	9.947	3.71	0.00
Stanton	34.493	6.26	0.00	1.273	0.43	0.67	-15.880	-5.91	0.00	11.496	2.32	0.02
Stevens	26.067	5.85	0.00	3.648	1.29	0.20	-12.496	-4.96	0.00	28.842	5.91	0.00
Sumner	153.108	13.70	0.00	0.243	0.31	0.76	-6.232	-2.85	0.00	11.804	3.38	0.00
Thomas	72.860	10.08	0.00	7.119	2.37	0.02	-12.165	-5.07	0.00	9.633	2.32	0.02
Trego	28.249	5.99	0.00	-1.312	-0.84	0.40	-12.218	-5.06	0.00	6.296	2.03	0.04
Wabaunsee	-1.835	-0.71	0.48	-0.138	-0.20	0.84	-8.939	-4.92	0.00	-0.206	-0.20	0.84
Wallace	26.996	5.84	0.00	-0.139	-0.07	0.95	-13.918	-5.71	0.00	2.548	0.77	0.44
Washington	28.523	8.73	0.00	1.627	1.32	0.19	-2.589	-1.18	0.24	18.094	6.48	0.00
Wichita	42.591	7.83	0.00	-1.655	-0.72	0.47	-15.314	-5.96	0.00	10.610	2.35	0.02
Wilson	4.835	2.13	0.03	0.351	0.60	0.55	-2.130	-1.09	0.28	1.781	1.68	0.09
Woodson	-5.120	-2.74	0.01	-0.162	-0.34	0.73	-7.330	-4.20	0.00	-0.917	-1.05	0.29

Table B.0.18. Fixed Effects Yield Response County Constant Terms

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Constant	32.904	1.14	0.25	104.178	3.77	0.00	11.709	1.19	0.23	23.801	1.15	0.25
Anderson	3.143	1.50	0.13	-3.520	-0.92	0.36	1.543	0.98	0.33	3.608	1.15	0.25
Atchison	1.065	0.48	0.63	-4.648	-0.90	0.37	5.620	3.63	0.00	8.744	2.66	0.01
Barber	-12.496	-3.85	0.00	32.561	4.16	0.00	8.521	2.99	0.00	-18.317	-4.67	0.00
Barton	-5.849	-1.83	0.07	40.779	6.94	0.00	11.763	5.32	0.00	1.412	0.34	0.73
Bourbon	2.134	0.99	0.32	-4.723	-1.09	0.28	0.740	0.46	0.65	1.879	0.55	0.58
Brown	8.461	3.34	0.00	9.431	1.60	0.11	10.735	6.19	0.00	18.902	5.36	0.00
Butler	-2.534	-1.15	0.25	-7.823	-1.93	0.05	-0.895	-0.49	0.63	-6.026	-1.68	0.09
Chase	-6.558	-3.22	0.00	-11.339	-2.57	0.01	1.287	0.71	0.48	-9.054	-2.57	0.01
Chautauqua	-7.005	-3.04	0.00	-9.226	-2.23	0.03	-1.916	-1.01	0.31	-14.416	-4.36	0.00
Cherokee	6.485	2.90	0.00	9.378	2.05	0.04	0.584	0.32	0.75	4.610	1.22	0.22
Cheyenne	-13.232	-3.03	0.00	29.857	3.82	0.00	11.133	3.71	0.00	-6.539	-1.08	0.28
Clark	-21.914	-5.30	0.00	30.906	1.56	0.12	8.372	2.60	0.01	-3.755	-0.56	0.57
Clay	-2.665	-1.02	0.31	31.420	6.71	0.00	5.018	2.62	0.01	3.975	0.97	0.33
Cloud	-5.487	-1.82	0.07	29.213	5.72	0.00	3.727	1.85	0.07	4.562	1.04	0.30
Coffey	-1.474	-0.65	0.51	-6.145	-1.37	0.17	0.219	0.14	0.89	-0.955	-0.31	0.76
Comanche	-19.791	-6.08	0.00	42.171	7.07	0.00	6.612	2.32	0.02	-18.315	-4.25	0.00
Cowley	-4.725	-2.03	0.04	-19.427	-4.03	0.00	-0.436	-0.23	0.82	-8.774	-2.69	0.01
Crawford	5.848	2.73	0.01	-1.171	-0.27	0.79	1.224	0.81	0.42	4.990	1.63	0.10
Decatur	-11.657	-2.79	0.01	-28.678	-3.88	0.00	6.763	2.27	0.02	-7.865	-1.43	0.15
Dickinson	-3.063	-1.04	0.30	-16.733	-2.86	0.00	-0.589	-0.31	0.76	-8.661	-2.23	0.03
Doniphan	5.265	2.09	0.04	8.267	1.18	0.24	13.169	7.95	0.00	15.203	3.89	0.00
Douglas	2.988	1.48	0.14	2.144	0.44	0.66	7.294	3.97	0.00	4.476	1.38	0.17
Edwards	-9.221	-3.27	0.00	47.747	7.63	0.00	17.136	7.40	0.00	-2.991	-0.74	0.46
Elk	-6.030	-2.92	0.00	-9.614	-1.73	0.08	2.762	1.51	0.13	-9.694	-2.81	0.01
Ellis	-14.762	-3.72	0.00	-17.570	-1.48	0.14	-1.978	-0.54	0.59	-19.843	-3.58	0.00
Ellsworth	-13.388	-4.09	0.00	-15.596	-2.37	0.02	-3.616	-1.53	0.13	-7.330	-1.63	0.10

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Finney	-2.043	-0.50	0.61	56.530	7.24	0.00	14.614	5.58	0.00	10.671	1.98	0.05
Ford	-6.922	-1.89	0.06	59.314	8.75	0.00	17.317	6.91	0.00	7.209	1.46	0.14
Franklin	3.797	1.84	0.07	0.422	0.09	0.93	4.586	2.50	0.01	-2.184	-0.61	0.54
Geary	-5.960	-2.13	0.03	14.664	2.88	0.00	3.961	1.85	0.07	-4.672	-1.11	0.27
Gove	-12.211	-3.08	0.00	-0.562	-0.08	0.94	4.804	1.77	0.08	-9.330	-1.75	0.08
Graham	-14.338	-3.75	0.00	7.890	1.12	0.27	6.222	1.73	0.08	-11.880	-2.01	0.04
Grant	-0.677	-0.19	0.85	55.876	7.39	0.00	13.376	4.34	0.00	3.766	0.66	0.51
Gray	-2.053	-0.58	0.56	66.680	9.04	0.00	18.319	7.41	0.00	13.897	2.80	0.01
Greeley	-13.994	-3.21	0.00	23.393	2.81	0.01	2.831	0.91	0.36	-9.538	-1.56	0.12
Greenwood	-3.896	-1.89	0.06	-9.778	-2.09	0.04	2.071	1.11	0.27	-10.171	-2.73	0.01
Hamilton	-19.151	-4.42	0.00	45.863	4.64	0.00	7.627	2.55	0.01	-6.901	-1.09	0.28
Harper	-6.405	-1.71	0.09	-7.916	-0.85	0.39	6.211	1.99	0.05	-17.753	-3.74	0.00
Harvey	-2.107	-0.86	0.39	28.533	5.75	0.00	8.024	3.50	0.00	-1.084	-0.24	0.81
Haskell	2.172	0.61	0.54	63.816	7.62	0.00	15.773	5.34	0.00	22.587	3.65	0.00
Hodgeman	-13.932	-4.01	0.00	34.062	5.13	0.00	9.465	3.53	0.00	-9.781	-1.98	0.05
Jackson	-3.069	-1.28	0.20	-10.278	-2.12	0.03	4.660	2.52	0.01	-3.197	-0.83	0.41
Jefferson	3.312	1.34	0.18	-1.587	-0.30	0.76	6.267	3.41	0.00	3.821	1.01	0.31
Jewell	-4.600	-1.34	0.18	22.955	3.67	0.00	5.594	2.49	0.01	9.523	1.93	0.05
Johnson	4.082	1.96	0.05	-8.513	-1.39	0.17	7.883	3.88	0.00	7.491	1.97	0.05
Kearny	-9.247	-2.42	0.02	40.181	5.10	0.00	11.222	3.82	0.00	0.261	0.05	0.96
Kingman	-9.171	-2.72	0.01	46.931	8.46	0.00	8.146	3.72	0.00	-15.729	-4.26	0.00
Kiowa	-11.926	-4.03	0.00	56.158	8.95	0.00	17.119	7.44	0.00	-4.866	-1.05	0.29
Labette	-1.632	-0.74	0.46	1.525	0.28	0.78	-2.134	-1.17	0.24	2.025	0.56	0.57
Lane	-13.690	-3.66	0.00	18.869	2.71	0.01	6.666	2.46	0.01	-7.968	-1.56	0.12
Leavenworth	2.027	0.99	0.32	-5.678	-1.01	0.31	5.752	3.16	0.00	1.506	0.43	0.67
Lincoln	-10.956	-3.24	0.00	-19.437	-2.63	0.01	-1.919	-0.85	0.40	-4.221	-0.90	0.37
Linn	1.582	0.71	0.48	-4.794	-1.12	0.26	2.423	1.42	0.16	-2.821	-0.84	0.40

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Logan	-17.601	-4.36	0.00	6.268	0.70	0.48	2.793	0.86	0.39	-8.844	-1.60	0.11
Lyon	-3.744	-1.63	0.10	-6.251	-1.47	0.14	2.621	1.63	0.10	-3.492	-0.99	0.32
Marion	-4.129	-1.57	0.12	-13.688	-2.78	0.01	-2.645	-1.39	0.17	-5.832	-1.49	0.14
Marshall	-0.642	-0.22	0.83	-5.624	-1.00	0.32	3.172	1.68	0.09	10.870	2.53	0.01
McPherson	-2.569	-0.74	0.46	40.293	7.88	0.00	5.937	3.21	0.00	-0.205	-0.05	0.96
Meade	-6.457	-2.09	0.04	62.099	8.44	0.00	15.013	5.68	0.00	17.968	3.01	0.00
Miami	3.581	1.66	0.10	-6.185	-1.39	0.17	5.422	3.24	0.00	-1.868	-0.55	0.58
Mitchell	-4.810	-1.42	0.16	18.497	3.24	0.00	1.270	0.55	0.59	0.144	0.03	0.98
Montgomery	-1.126	-0.56	0.57	-6.136	-1.66	0.10	-1.246	-0.72	0.47	-8.311	-2.45	0.01
Morris	-9.025	-3.61	0.00	-17.419	-3.45	0.00	-1.401	-0.73	0.47	-12.718	-3.27	0.00
Morton	-10.347	-2.72	0.01	31.609	4.53	0.00	8.283	2.93	0.00	-12.694	-2.22	0.03
Nemaha	2.045	0.77	0.44	-5.218	-0.94	0.35	4.066	2.11	0.04	5.248	1.29	0.20
Neosho	-0.136	-0.07	0.95	-3.811	-0.96	0.34	-1.242	-0.77	0.44	0.594	0.19	0.85
Ness	-14.011	-3.59	0.00	-9.648	-1.14	0.25	-0.448	-0.13	0.89	-14.877	-2.86	0.00
Norton	-14.142	-3.64	0.00	-14.820	-1.95	0.05	2.441	0.73	0.47	-3.801	-0.67	0.50
Osage	-1.091	-0.47	0.64	-9.119	-1.93	0.05	2.369	1.40	0.16	2.817	0.77	0.44
Osborne	-10.149	-3.01	0.00	20.671	3.19	0.00	3.618	1.48	0.14	0.752	0.16	0.88
Ottawa	-7.765	-2.44	0.02	12.900	2.25	0.03	0.330	0.15	0.88	-5.127	-1.28	0.20
Pawnee	-8.094	-2.57	0.01	40.730	6.35	0.00	14.393	6.17	0.00	6.816	1.46	0.15
Phillips	-10.876	-3.00	0.00	0.272	0.03	0.97	2.629	0.99	0.32	-2.171	-0.44	0.66
Pottawatomie	1.168	0.50	0.62	10.681	2.20	0.03	8.663	4.58	0.00	4.185	1.05	0.29
Pratt	-6.538	-2.24	0.03	49.591	9.02	0.00	18.174	7.93	0.00	-6.161	-1.51	0.13
Rawlins	-9.515	-2.21	0.03	-10.154	-1.28	0.20	8.164	2.52	0.01	-7.327	-1.35	0.18
Reno	-3.814	-1.03	0.30	27.451	5.54	0.00	8.939	4.28	0.00	-5.258	-1.19	0.23
Republic	-2.110	-0.72	0.47	24.150	4.76	0.00	8.524	4.45	0.00	3.032	0.73	0.47
Rice	-3.916	-1.36	0.17	37.156	6.55	0.00	6.682	2.79	0.01	0.866	0.21	0.83
Riley	-1.754	-0.73	0.47	8.899	1.87	0.06	7.021	3.67	0.00	4.496	1.10	0.27
Rooks	-15.347	-4.18	0.00	-7.391	-0.78	0.44	-5.450	-2.05	0.04	-7.312	-1.37	0.17

	Wheat			Corn			Soybean			Sorghum		
	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t	Coef.	t	P>t
Rush	-14.752	-4.31	0.00	15.040	2.20	0.03	3.943	1.44	0.15	-9.005	-2.04	0.04
Russell	-12.100	-3.66	0.00	-39.646	-4.37	0.00	-3.793	-1.26	0.21	-11.762	-2.62	0.01
Saline	-9.488	-3.02	0.00	3.100	0.51	0.61	-0.326	-0.15	0.88	-6.829	-1.59	0.11
Scott	-4.863	-1.34	0.18	24.054	3.44	0.00	9.173	3.34	0.00	6.568	1.26	0.21
Sedgwick	-2.453	-0.76	0.45	29.167	5.42	0.00	11.186	5.27	0.00	-8.292	-1.94	0.05
Seward	-5.634	-1.62	0.10	54.341	7.10	0.00	15.062	5.08	0.00	-2.375	-0.39	0.70
Shawnee	0.173	0.07	0.94	8.255	1.59	0.11	7.483	4.22	0.00	-0.348	-0.10	0.92
Sheridan	-7.120	-1.89	0.06	36.089	5.10	0.00	15.771	5.77	0.00	4.339	0.82	0.41
Sherman	-11.600	-2.61	0.01	29.182	3.82	0.00	11.470	4.23	0.00	-2.840	-0.52	0.60
Smith	-3.008	-0.94	0.35	4.268	0.63	0.53	3.465	1.49	0.14	7.640	1.57	0.12
Stafford	-3.327	-1.18	0.24	36.548	5.67	0.00	15.712	7.18	0.00	-4.610	-1.03	0.30
Stanton	-4.272	-1.08	0.28	54.169	6.10	0.00	9.645	3.08	0.00	6.987	1.07	0.29
Stevens	0.442	0.12	0.90	56.045	7.10	0.00	9.626	3.44	0.00	-9.418	-1.70	0.09
Sumner	0.143	0.03	0.98	-10.143	-1.66	0.10	-0.674	-0.32	0.75	-18.498	-4.81	0.00
Thomas	-9.948	-2.24	0.03	39.179	5.02	0.00	11.101	4.12	0.00	-3.742	-0.72	0.47
Trego	-16.483	-4.11	0.00	16.962	1.45	0.15	-1.383	-0.30	0.77	-22.607	-3.26	0.00
Wabaunsee	-2.921	-1.21	0.23	-0.364	-0.07	0.95	4.264	2.27	0.02	0.251	0.07	0.95
Wallace	-11.029	-3.04	0.00	22.999	3.10	0.00	5.736	2.03	0.04	0.300	0.05	0.96
Washington	-1.300	-0.48	0.63	-0.831	-0.16	0.87	4.168	2.05	0.04	8.193	1.86	0.06
Wichita	-6.923	-1.74	0.08	32.275	4.14	0.00	7.377	2.62	0.01	15.295	2.63	0.01
Wilson	0.063	0.03	0.98	0.618	0.17	0.87	0.811	0.55	0.58	6.323	1.82	0.07
Woodson	-0.855	-0.42	0.67	-7.631	-2.04	0.04	-0.409	-0.25	0.80	-0.160	-0.05	0.96

Appendix C - Further Weather and Climate Simulation Results

Table C.0.19. Estimated Corn Yields Given Changes in Temperature or Precipitation[38]

	Temperature			Precipitation		
Change	**OLS**	**FE**	**SUR**	**OLS**	**FE**	**SUR**
-5	139.1821	114.4175	149.2381	109.1086	108.9043	133.381
-4	132.3266	114.121	147.498	109.7011	109.6215	133.7515
-3	126.1693	113.7513	145.203	110.2751	110.3101	134.0975
-2	120.7101	113.3084	142.3529	110.8307	110.9698	134.4188
-1	115.9492	112.7923	138.9479	111.3678	111.6008	134.7156
0	111.8865	112.2031	134.9878	111.8865	112.2031	134.9878
1	108.522	111.5407	130.4727	112.3868	112.7766	135.2354
2	105.8558	110.8051	125.4026	112.8686	113.3213	135.4584
3	103.8877	109.9963	119.7775	113.332	113.8373	135.6568
4	102.6178	109.1144	113.5974	113.7769	114.3245	135.8306
5	102.0462	108.1593	106.8622	114.2034	114.7829	135.9799

Table C.0.20. Estimated Soybean Yields Given Changes in Temperature or Precipitation

	Temperature			Precipitation		
Change	**OLS**	**FE**	**SUR**	**OLS**	**FE**	**SUR**
-5	40.3878	33.02432	34.29793	30.28486	30.65678	31.83269
-4	38.52105	32.99303	34.49862	30.87732	31.1867	32.28363
-3	36.82456	32.98488	34.56276	31.45134	31.6959	32.71942
-2	35.29833	32.99986	34.49035	32.00693	32.1844	33.14006
-1	33.94237	33.03799	34.28139	32.54406	32.65218	33.54555
0	32.75668	33.09925	33.93589	33.06276	33.09925	33.93589
1	31.74125	33.18366	33.45384	33.56301	33.52562	34.31108
2	30.89608	33.29121	32.83524	34.04482	33.93127	34.67112
3	30.22118	33.42189	32.08009	34.50819	34.31622	35.01601
4	29.71654	33.57572	31.1884	34.95311	34.68046	35.34576
5	29.38217	33.75269	30.16015	35.3796	35.02398	35.66035

[38] Precipitation is treated differently than temperature, as temperature is the average for each growing season while precipitation is the summation of the season. Accounting for a one inch increase in rainfall annually would equate to a 0.25 inch increase in each quarter growing season. With wheat production, the increase would be in fifths, were a one inch increase annually is a 0.2 inches each season.

Table B.0.21. Estimated Sorghum Yields Given Changes in Temperature or Precipitation

	Temperature			Precipitation		
Change	**OLS**	**FE**	**SUR**	**OLS**	**FE**	**SUR**
-5	74.55672	68.96356	77.6463	67.31989	62.66246	70.94527
-4	73.52628	68.02533	77.28205	67.91235	63.9485	71.88012
-3	72.53601	67.51927	76.86464	68.48637	65.18468	72.78235
-2	71.5859	67.44538	76.39405	69.04196	66.37102	73.65197
-1	70.67596	67.80366	75.87029	69.57909	67.50749	74.48897
0	69.80618	68.59411	75.29335	70.09779	68.59411	75.29335
1	68.97658	69.81673	74.66325	70.59804	69.63087	76.06513
2	68.18714	71.47152	73.97998	71.07985	70.61778	76.80428
3	67.43786	73.55848	73.24353	71.54322	71.55483	77.51082
4	66.72875	76.07762	72.45391	71.98814	72.44202	78.18475
5	66.05981	79.02892	71.61112	72.41463	73.27936	78.82605

Table B.0.22. Estimated Wheat Yields Given Changes in Temperature or Precipitation

	Temperature			Precipitation		
Change	**OLS**	**FE**	**SUR**	**OLS**	**FE**	**SUR**
-5	40.30925	40.36829	43.24679	39.02256	38.76479	43.99662
-4	40.49894	40.45753	43.56139	38.93045	38.70944	43.80315
-3	40.40953	40.30446	43.68795	38.82852	38.64416	43.60021
-2	40.04103	39.90909	43.62647	38.71678	38.56895	43.38778
-1	39.39344	39.27142	43.37696	38.59523	38.48379	43.16588
0	38.46676	38.39144	42.93942	38.46387	38.3887	42.9345
1	37.26098	37.26916	42.31383	38.32269	38.28368	42.69364
2	35.77611	35.90457	41.50022	38.17169	38.16871	42.44329
3	34.01214	34.29768	40.49856	38.01089	38.04381	42.18347
4	31.96909	32.44849	39.30888	37.84027	37.90898	41.91417
5	29.64694	30.35699	37.93115	37.65983	37.7642	41.63539

Table B.0.23. Average County Supply for Corn Given Changes in Climate Temperature or Precipitation, Bushels

	Temperature			Precipitation		
Change	OLS	FE	SUR	OLS	FE	SUR
-5	2608.38	2606.23	2600.478	2668.408	2542.411	2967.68
-4	2584.837	2584.969	2586.772	2634.783	2538.904	2936.969
-3	2563.769	2567.122	2570.773	2602.68	2536.297	2906.02
-2	2545.135	2552.663	2552.541	2572.051	2534.583	2874.814
-1	2528.899	2541.565	2532.141	2542.848	2533.754	2843.328
0	2515.022	2533.8	2509.634	2515.022	2533.8	2811.541
1	2503.468	2529.34	2485.085	2488.527	2534.714	2779.428
2	2494.201	2528.154	2458.555	2463.313	2536.488	2746.97
3	2487.185	2530.213	2430.108	2439.335	2539.111	2714.142
4	2482.385	2535.486	2399.808	2416.544	2542.576	2680.921
5	2479.769	2543.94	2367.718	2394.895	2546.875	2647.285

Table B.0.24. Average County Supply for Soybeans Given Changes in Climate Temperature or Precipitation, Bushels

	Temperature			Precipitation		
Change	OLS	FE	SUR	OLS	FE	SUR
-5	808.9238	775.3187	1208.133	828.3109	762.0911	893.8597
-4	799.1141	769.464	1201.989	819.4017	758.7033	958.1437
-3	791.2582	764.6149	1196.516	810.0338	756.3957	1019.37
-2	785.3478	760.7663	1191.693	800.2226	755.178	1077.459
-1	781.3746	757.9134	1187.5	789.9831	755.06	1132.333
0	779.3306	756.0513	1183.914	779.3306	756.0513	1183.914
1	779.208	755.1748	1180.914	768.2803	758.1613	1232.122
2	780.9994	755.2787	1178.48	756.8473	761.3995	1276.878
3	784.6976	756.3578	1176.589	745.0471	765.775	1318.104
4	790.2955	758.4066	1175.221	732.8946	771.297	1355.721
5	797.7865	761.4197	1174.353	720.4053	777.9745	1389.648

Table B.0.25. Average County Supply for Wheat Given Changes in Climate Temperature or Precipitation, Bushels

	Temperature			Precipitation		
Change	OLS	FE	SUR	OLS	FE	SUR
-5	4184.909	4361.286	4404.65	4147.32	4153.014	4333.809
-4	4144.44	4243.835	4369.062	4130.209	4115.868	4327.054
-3	4112.087	4148.275	4341.699	4113.201	4080.438	4321.085
-2	4087.756	4073.772	4322.454	4096.297	4046.709	4315.901
-1	4071.356	4019.432	4311.219	4079.495	4014.666	4311.501
0	4062.794	3984.296	4307.884	4062.794	3984.296	4307.884
1	4061.985	3967.342	4312.34	4046.195	3955.583	4305.049
2	4068.842	3967.485	4324.481	4029.696	3928.511	4302.996
3	4083.282	3983.574	4344.197	4013.297	3903.065	4301.723
4	4105.222	4014.399	4371.38	3996.996	3879.227	4301.231
5	4134.585	4058.681	4405.922	3980.793	3856.982	4301.518

Table B.0.26. Average County Supply for Sorghum Given Changes in Climate Temperature or Precipitation, Bushels

	Temperature			Precipitation		
Change	OLS	FE	SUR	OLS	FE	SUR
-5	2723.716	2671.58	3024.821	2562.918	2376.104	3144.13
-4	2708.527	2655.466	3044.165	2588.831	2426.628	3125.276
-3	2695.172	2641.357	3055.192	2612.187	2475.483	3105.307
-2	2683.652	2629.251	3057.937	2632.904	2522.569	3084.223
-1	2673.963	2619.145	3052.434	2650.903	2567.787	3062.025
0	2666.105	2611.036	3038.713	2666.105	2611.036	3038.713
1	2660.077	2604.921	3016.805	2678.429	2652.218	3014.289
2	2655.877	2600.796	2986.736	2687.795	2691.231	2988.752
3	2653.505	2598.655	2948.529	2694.125	2727.974	2962.103
4	2652.961	2598.496	2902.208	2697.34	2762.347	2934.343
5	2654.242	2600.314	2847.792	2697.36	2794.246	2905.472