Producer Expectations and the Extensive Margin in Grain Supply Response

David Boussios and Andrew Barkley

Grain supply is the joint effect of both area and yield; however, research often targets either one or the other. The research presented here estimates the complete supply elasticity of grains using novel approaches to approximate producers' price and weather expectations on both yield and acres planted. The results from this approach combining acreage and yield show the negative impact of expanded production on average yields and the supply response. Additionally, the research extends previous methods of approximating producers' price expectations through the use of historical basis prices.

Key Words: corn, extensive margin, producer expectations, sorghum, soybeans, supply elasticity, supply response, wheat

Measuring how grain supplies are affected by weather, climate, and prices is imperative for policymakers and agribusinesses, and research that can quantify supply-production decisions will create more informed, less volatile markets. Greater understanding of commodity supply forces is timely, important, and interesting since a number of categorical changes have occurred in commodity markets in recent years. Traditionally, research on agricultural supply responses has been divided into two components: acreage allocation and the impact of biophysical and economic variables on crop yields. However, as Houck and Gallagher (1976) highlighted, there is a downside to the separation of supply responses: "taking acreage response estimates as approximations to total supply elasticities is to seriously underestimate the price responsiveness of corn production" (p. 734). While individual acreage and yield analyses are important for examinations of land use and public policy, they are less effective for understanding commodity responses. McDonald and Sumner (2003) further elaborated on this point in an analysis of rice farmers. Through careful quantification of acreage and yield responses, we present a method that can more accurately and completely measure supply responses for agricultural commodities and apply it to county-level production of wheat, corn, soybeans, and sorghum (milo) in Kansas for 1977 through 2007.

A fundamental issue in research on agricultural production relates to the heterogeneity of land (Just 2000, Pope and Just 2003). The impact of heterogeneity on commodity supply responses is important and has been

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studied in some detail using responses of both acreage and yields (Choi and Helmberger 1993, Hardie and Parks 1997, Lichtenberg 1989, Miller and Plantinga 1999, Orazem and Miranowski 1994, Schlenker, Hanemann, and Anthony 2004). Those methods accounted for the heterogeneity within their respective researched portions of the supply response. However, in translating the results of those analyses to a more complete supply response, one must assume a homogeneous response across the other elements that make up the supply of the commodity, an assumption that entirely ignores the important relationship in production between acres planted and yields generated.

In this research, we develop a recursive model to estimate total supply in which the number of acres planted is determined prior to analyzing the yield response following Choi and Helmberger (1993) and Houck and Gallagher (1976). By including acreage responses within the yield responses, we can more accurately estimate how total supply responds to economic and biophysical variables by incorporating the impact of expansion on the extensive margin for average yield responses. The increasing importance of further understanding the impacts of the extensive margin is evident from the 41 percent increase in the number of acres planted to corn in Kansas between 1997 and 2007. While researchers have established hypotheses about and made theoretical predictions of negative impacts of increasing acreage on yields, most previous studies have not successfully quantified those effects.

Researchers also have increasingly focused on the impacts of biophysical changes on yield responses due to greater awareness of climate change (Huang and Khanna 2010, McCarl, Villavicencio, and Wu 2008, Kaufmann and Snell 1997). However, ignoring the responsiveness of producers to switching crops omits an integral element of yield and supply responses. Producers make decisions based on expectations of yields and outputs. If they anticipate changes in climate that will impact yields, they will alter their planting decisions. Thus, it is important to analyze how producers' expectations about the climate and yields interact with their production decisions.

Increasing uncertainty brought on by climate change and volatility of prices in commodity markets further bolsters the importance of understanding producer expectations. Given the relatively long period between planting and harvesting, production decisions are based largely on expectations about future outcomes. Nerlove (1956) was keen to examine the importance of expectations in nonstationary markets. Subsequently, that work was extended through the use of commodity futures markets to quantify market perceptions of likely future spot prices (Chavas, Pope, and Kao 1983, Gardner 1976, Morzuch, Weaver, and Helmberger 1980, Orazem and Miranowski 1994). The extension was successful in estimating those expectations, but increases in commodity volatility and changes in the market recently (Wright 2011) have required development of new, more comprehensive methods for estimating producer expectations.[1]

Producers base their price expectations and thus production decisions on a variety of price signals, including current commodity market prices and the

[1] Perceptions of risk also certainly play a role in agricultural supply responses; however, efforts to quantify the impacts of risk have met with limited success. Early models attempted to analyze risk using existing research methods (Chavas and Holt 1990, Huang and Khanna 2010, Lin and Dismukes 2007), and their results were not robust and were generally inconclusive. Furthermore, analyses of risk using aggregate-level data are likely to generate incorrect estimates (Just and Weninger 1999).

performance of those prices historically. Divergences between futures prices at planting and at harvesting erode the confidence of producers in using futures prices as accurate expectations. Interpretion of changes in beliefs about prices is important for supply analyses because beliefs influence production decisions. Basis prices, the difference between the cash price and the futures price, provide one way to measure those perceptions. In this study, we analyze the four most important grain crops in Kansas; corn, soybeans, sorghum, and wheat harvested for grain accounted for 97.3 percent of all of the state's harvested acres (U.S. Department of Agriculture (USDA) 2008). We present a cross-sectional time series for 105 counties for 1977 through 2007.

Theoretical Perspective

Firms maximize profit based on expected costs and returns given their production functions, and firm-level profit can be defined as

$$\sum_{i=1}^{4} \pi_i = \sum_{i=1}^{4} P_i \times A_i \times Y_i - C_i \times A_i - F. \tag{1}$$

Profit (π) is equal to total revenue minus total cost. The revenue function is defined by output prices (P) multiplied by yield per acre (Y) and acres planted (A). The cost function is the per-acre marginal cost (C) multiplied by the number of acres planted plus fixed costs (F). The equation is indexed over i, which depicts the variety of crop choices available to the producer. We restrict the choices available to the four primary crops planted within Kansas (corn, soybeans, sorghum, and wheat). In an agricultural context where actual production is unknown due to long production horizons, firms base their decisions on expectations about the future rather than on known outcomes. Since expected profit is maximized across acres planted, the firm-level choice is restricted to which crop(s) to plant. Differentiating equation 1 with respect to acres for each crop and implicitly solving the first-order conditions for the optimized quantity of acres planted results in the following function:

$$A_i^* = A_i^* (P_i, Y_i, C_i) \tag{2}$$

where the profit-maximizing number of acres planted to each crop is a function of expected output and input prices and yields. The relationship of acres planted to exogenous expectations *a priori* follows that of a normal good. For own-price and own-yield, the marginal effects are positively related while the cross-effects are negative due to substitution. The marginal effects with respect to cost are expected to be negative.

When quantifying the impacts of producer expectations on planting decisions, one must extend equation 2 to more accurately measure their beliefs:

$$A_i^* = A_i^* (PX_i, BS_i, E(Y_i), E(W), PF_i, LA_i). \tag{3}$$

Price expectations are defined by future prices (PX) and basis prices (BS). Expectations about crop yields ($E(Y)$) and weather ($E(W)$) are derived from historically observed yields and weather, respectively. Input costs are simplified in the model by using fertilizer prices (PF). Large levels of capital are required for production that may limit the profitability of switching crops every season. Lagged acreage (LA) is included in the model to account for those fixed costs and for producer preferences, which may limit the substitutability of short-run planting options.

As previously noted, grain supply does not depend solely on acreage decisions. The literature's tendency to emphasize acreage responses over yield responses ignores a central tenet of agricultural supply. Quantifying the sensitivity of yield to economic factors, planting decisions, and weather allows us to more accurately estimate supply responses. In our model so far, yield is assumed to be constant in equation 1 as expected yield, which allows for optimized values of acres planted in equation 2. In practice, actual yields are expected to vary due to weather and price signals. The yield response model similarly follows Choi and Helmberger (1993) in that planting decisions are determined prior to yield response:

$$Y_i^* = Y_i^*(PX_i, BS_i, PF_i, A_i^*, A\%_i, W). \tag{4}$$

Crop yields are a function of price, total acres planted (A), the percent of total planted acres planted to that crop within that respective county ($A\%$), and actual weather (W). Some previous studies have analyzed the price effects on supply using homogeneous price assumptions in which prices were measured as relative rather than actual values of input and output prices. While that method follows from theoretical production considerations, the homogeneity of prices may not strictly hold in practical application since the marginal return to inputs likely changes over time. Furthermore, separation of the prices allows for more direct interpretation of producer responses.

We include both acres and percent of acres in the yield model because they reflect separate indicators of the yield response. The traditional relationship between acres planted and average yield is expectedly negative. Profit maximization theory predicts that the producer first brings the highest quality land into production so each additional acre planted thereafter is of relatively inferior quality and thus reduces the measured average yield. An additional term this research adds to traditional yield response analysis is the percent of total planted acres in the county devoted to the crop. This variable is included to empirically account for potential differences in counties' comparative production advantages and for omitted variables such as soil quality that are not captured in the traditional acres-planted variable. For example, a county may often specialize or proportionally grow more of a specific crop because it has a relative advantage in producing that crop. The specialization or relative advantage may be due to climatic conditions, soil quality, producer knowledge, and other regional characteristics, all of which directly influence production of each crop. Excluding this variable would omit differences in production capabilities and the relative advantage of some crops in specific growing areas, and this effect would likely bias total acres planted within a panel analysis.

Climate and weather affect each supply response component differently. Weather expectations impact producers' input use and capital expenditures and the suitability of particular crops at a given location. Actual weather, however, directly affects annual yields.

In measuring the full supply responsiveness of grain to changes in price, we can derive supply elasticities. The total amount of grain supplied (TS) is the yield per acre multiplied by the number of acres planted. To measure the response of supply to prices, one must differentiate equations 3 and 4 with respect to price. Supply is directly affected by changes in price through both yield and acreage responses, but yield is also indirectly affected by the acreage response represented in equation 4. The marginal impact of a change in price on total supply can be derived as

$$\frac{\partial TS}{\partial PX} = \frac{\partial TS}{\partial A}\frac{\partial A}{\partial PX} + \frac{\partial TS}{\partial Y}\frac{\partial Y}{\partial PX} + \frac{\partial TS}{\partial Y}\frac{\partial Y}{\partial A}\frac{\partial A}{\partial PX}. \tag{5}$$

This function can be written as an own-price elasticity:

$$\varepsilon_{SR\ TS,PX} = \varepsilon_{A,PX} \times (1 + \varepsilon_{Y,A}) + \varepsilon_{Y,PX}. \tag{6}$$

When the optimal number of acres is imbedded in the yield function, equation 6 differs from traditional own-price total-supply response models by $\varepsilon_{A,PX} \times \varepsilon_{Y,A}$, the indirect effect of production on the margin. Each short-run elasticity with respect to price is expected to be positive but $\varepsilon_{Y,A}$ is expected to be negative. A price increase is expected to raise the number of acres planted, which increases total supply. However, the expansion in acres also affects the average yield so the yield-acreage elasticity should mitigate a portion of the own-price acreage elasticity.

We estimate the long-run supply elasticities using distributed lags (Nerlove and Addison 1958). Prior research has emphasized the importance of distributed lags in measuring producers' aversion or inability to switch crops. The long-run supply elasticity is given as

$$\varepsilon_{LR\ TS,PX} = \frac{\varepsilon_{A,PX}}{1 - \varepsilon_{A,LA}} \times \left(1 + \varepsilon_{Y,A}\right) + \varepsilon_{Y,PX}. \tag{7}$$

The total supply elasticity with respect to input prices is similarly estimated, and production theory suggests that it will be negative.

Data and Method

We obtained county acreage and yield data for the four crops in the study from the USDA National Agricultural Statistics Service (NASS) (2011) and weather data from the Kansas State Weather Data Library (2011) and the National Climatic Data Center (NCDC) (2011). Table 1 presents the variables included in the supply response models. A profit-maximizing producer bases planting and crop management decisions on expected revenues and costs. The unknown parameters in the decision are prices and weather. While there is a futures market for most crops in which expected prices can be inferred, there is no market that directly interprets producers' weather expectations. Thus, farmers must base production decisions on observed weather. In the county-level data used in this study, temperatures are monthly means and precipitation is reported as the monthly sum.[2] We define producer climate expectations as ten-year lagged rolling-average precipitation amounts and temperatures.[3] For the acreage model, we analyze producer expectations for the entire period of crop

[2] Missing temperature values (2.6 percent of all observations) were estimated using ordinary least square regression with county and year dummy variables.

[3] The ten-year interval was selected to capture the fact that climate perceptions are likely based on longer historical trends rather than on seasonal shifts. With a ten-year average, a significant one-year anomaly is less likely to impact producer expectations. Future studies could analyze the impact of weather anomalies on producer expectations.

Table 1. Crop Supply Response Model: Variable Descriptions and Sources

Code	Description	Source
PF	Price of anhydrous ammonia before planting	Economic Research Service
PX	Futures price of crop before planting for contract after harvest	Chicago Bd of Trade, Kansas City Bd of Trade
BPX	Three-year lagged basis price	Kansas State Ag Manager
A	Total acres planted in thousand acres	National Agricultural Statistics Service
Acreage Model		
PS_i	Future price of substitute crop, $i = 1,2$	Chicago Bd of Trade, Kansas City Bd of Trade
LA	Previous year's total acres planted in thousand acres	National Agricultural Statistics Service
Y_i	Five-year lagged county average yield, $i = 1,2,3,4$	National Agricultural Statistics Service
$E(WP)$	Ten-year lagged average annual total precipitation in inches, quadratic form	Kansas State Weather Data Library
$E(WT)$	Ten-year lagged average annual mean temperature in °F, quadratic form	National Climatic Data Center
Yield Model		
Y	County yield	National Agricultural Statistics Service
T	Time trend, quadratic	—
A%	Share (percent) of crop of interest in total acres planted of the four crops	National Agricultural Statistics Service
WP_i	Difference from ten-year average precipitation for specific season, quadratic, $i = 1,2,3,4$	Kansas State Weather Data Library
WT_i	Difference from ten-year average temperature for specific season, quadratic, $i = 1,2,3,4$	National Climatic Data Center

Note: All prices are deflated at 2007 values (Bureau of Labor Statistics 2011).

production, which is defined as two months prior to planting through harvest.[4] Since planting decisions are based on general locations and weather trends, the weather data are aggregated over the entire period of crop production. We use rolling averages because we expect that planting decisions are primarily impacted only by persistent changes in weather patterns rather than by seasonal deviations.

For the yield model, the crop production period is divided into four distinct phases (see Table 2). Precipitation and temperature during each stage of crop growth are incorporated into the model as the difference between the ten-year historical average for each phase and the observed values for the year. The ten-year historical average represented producers' expectations about

[4] The climate expectations are in quadratic form because there is expected nonlinearity of climates suitable for the selected crops.

Table 2. Definitions of Crop Growing Periods

	Growing Period				
Crop	**1**	**2**	**3**	**4**	**5**
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[a]

[a] Thirteen months—from July of the preceding year through July of the crop year.

Source: Kansas State University Agricultural Experiment Station and Cooperative Extension Service, *Corn* (2007), *Soybean* (1997), *Sorghum* (1998), *and Wheat* (1997) *Production Handbooks.*

climate, and we preferred this method to *ex post* methods because it allowed us to incorporate actual differences in average precipitation and temperature from producers' expectations and to quantify the effects of such divergences on yields.

The weather deviation data are county-specific. Region-specific impacts are important because many crucial decisions, including dates of planting and harvesting, depend on regional factors. When measuring a yield response, for example, the impact of decisions by a farmer in a relatively drier county that experiences an unusually wet spring will differ from those of a farmer in a relatively wet county that receives a typical amount of moisture even though traditional methods/variables would equate the measures and their marginal effects. Other methods, such as degree days, and numerous minimum/maximum relationships were considered; however, deviations from the mean promised to better capture producer expectations (Nelson and Dale 1978) and the model assumptions. The variables are in quadratic form since weather's effects on yields have been shown to be nonlinear (Schlenker and Roberts 2006).

In the model, the fertilizer price is the average price per ton paid by producers for anhydrous ammonia at planting (Economic Research Service (ERS) (2011).[5] Futures prices before planting for forward contracts after harvest were obtained from the Chicago Board of Trade (2011) for corn and soybeans and from the Kansas City Board of Trade (2011) for wheat.[6] Data for the spring crops are futures prices in March, prices for corn and sorghum are for December delivery, prices for soybeans are for November, and wheat prices are from September for July contracts the following year. The cross-prices for each crop are measured in the month of interest for that crop. Although wheat contracts in the spring crop analysis are measured only as March–July maturity, we assume that they

[5] Anhydrous ammonia was used instead of the commoly used USDA fertilizer price index because the annual index is believed to inaccurately reflect prices at planting. Annual prices are potentially influenced by other factors during the year and could be partially endogenous of acre and yield responses. Furthermore, ammonia (NH_3) is often a large factor in input costs, and a pairwise correlation test shows that the price of ammonia is highly correlated with prices for other fertilizers and thus is an effective price proxy.

[6] Since there is no sorghum futures market, prices were estimated by dividing the corn cash price at planting by the sorghum cash price and then multiplying that figure by the corn futures price. Given the high degree of substitutability of corn and sorghum in feed rations, producers often use corn prices to estimate sorghum values.

provide an accurate measure of producer perceptions of wheat as a substitute crop since fall plantings are impacted by spring decisions.

This study uses basis prices to quantify producer price expectations. If futures prices have historically overvalued or undervalued the crop prices at harvest, producers will adjust their perceptions of the efficiency and accuracy of futures prices in predicting harvest prices. In light of the large shifts in acreage and volatile prices seen in recent years (Wright 2011), producers use all information and make their decisions accordingly.

As noted by Hendricks (2011), price spikes at harvest have been followed by large shifts in acreage toward crops with upward trending prices. By including additional information on historic realizations of prices, models can more accurately reflect producer perceptions, which continually evolve and are critical for analysis of nonstationary markets. Basis prices are not new to studies of commodity supply; they have been used to measure impacts of price risk (Chavas and Holt 1990). We use basis prices to estimate producer price expectations with the basis prices measured as rolling three-year averages calculated as the difference between the state cash price at harvest (Kansas State Ag Manager 2011) and the pre-planting futures price. The three-year period for the rolling averages was chosen because it efficiently incorporates basis differences in individual years while not basing producers' expectations entirely on one year's experience.

In the acreage model, expected yields are measured as a lagged five-year average yield for the county.[7] Expected yields dramatically impact producers' estimates of the profitability of their crops. And with varying rates of technical agricultural advances for various crops, especially in terms of management practices and crop genetics, expectations of yield over time are changing, further signifying the relevancy of the variable across time. Omission of such expectations ignores relative per-acre values for each crop, and that omission reinforces the rationale for removing assumptions of homogeneous price relationships. To account for technology differences and other unknown factors over time, we include a quadratic time trend in the yield model.

Since we use panel data, we employ a fixed effects model to estimate the marginal effects of the variables on county production.[8] Tables 3 through 6 present summary statistics for the supply response models for wheat, corn, sorghum, and soybeans. Given the large differences in weather, county size, and amount of irrigation in the data set, the fixed effects model is assumed to be the best choice because it allows for heterogeneity across counties. While irrigation significantly alters yield expectations and producer decisions, it is difficult to quantify those impacts using aggregated data. In addition, because irrigation data is often inconsistently recorded and an assumption of homogeneity of

[7] Chavas and Holt (1990) quantified yield expectations by regressing actual yields on a trend variable. The five-year lagged average method used in this study was chosen for simplicity and because it explains producer expectations in specific counties. All of the lagged averages in our model are weighted equally across years. Future studies could analyze differences associated with various weighting methods. Our approach to weighting climate, basis prices, and yields accounts for producers' expectations of changes in those factors in the short term and in the long term.

[8] Hausman tests further supported use of a fixed effects model over a random effects model. As a reviewer pointed out, panel data models that include lagged dependent variables can present inconsistent results. Table A.1 in the appendix (available upon request from the authors) provides the results of an Arellano-Bond dynamic panel-data model. The significances and signs produced by that model were consistent with the results of our primary model, which further supports the methods used and the results.

Table 3. Summary Statistics for Wheat

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Both Models					
PF	2,732	382.24	115.73	238.75	673.47
PX	2,732	5.29	0.70	3.98	6.65
BPX	2,732	−0.71	0.67	−1.98	0.61
A	2,732	106.00	79.72	1.10	525.00
Acreage-specific Model					
PS1	2,732	3.71	0.60	2.49	5.37
PS2	2,732	9.25	1.49	5.48	12.91
LA	2,732	106.85	80.11	3.40	525.00
YC	2,732	104.19	31.86	44.60	193.20
YS	2,732	30.17	7.96	13.14	56.40
YM	2,732	63.15	11.81	34.00	101.40
YW	2,732	35.49	5.65	21.60	62.20
$E(WP)$	2,732	34.23	8.57	15.98	54.90
$E(WT)$	2,732	56.75	1.71	51.89	60.61
$E(WP)^2$	2,732	1,245.39	589.82	255.42	3,014.23
$E(WT)^2$	2,732	3,223.20	193.35	2,692.65	3,673.20
Yield-specific Model					
Y	2,732	35.88	9.67	9.00	80.00
T	2,732	16.53	8.58	1.00	31.00
T^2	2,732	346.89	284.97	1.00	961.00
A%	2,732	50.39	22.59	0.74	97.92
WP1	2,732	0.12	3.81	−8.59	20.58
WP2	2,732	−0.23	3.17	−8.79	19.75
WP3	2,732	−0.12	2.38	−7.71	12.35
WP4	2,732	−0.09	3.31	−9.08	16.70
WP5	2,732	0.20	4.00	−10.80	19.30
WT1	2,732	0.13	2.50	−6.71	8.48
WT2	2,732	−0.01	2.15	−6.74	6.32
WT3	2,732	0.17	3.01	−9.96	6.39
WT4	2,732	0.17	2.50	−8.53	5.91
WT5	2,732	0.04	2.21	−6.36	7.84
$WP1^2$	2,732	14.55	27.06	0.00	423.45
$WP2^2$	2,732	10.12	25.29	0.00	390.18
$WP3^2$	2,732	5.70	10.41	0.00	152.57
$WP4^2$	2,732	10.93	18.50	0.00	278.82
$WP5^2$	2,732	16.01	30.68	0.00	372.49
$WT1^2$	2,732	6.28	9.21	0.00	72.00
$WT2^2$	2,732	4.61	5.84	0.00	45.36
$WT3^2$	2,732	9.10	11.68	0.00	99.15
$WT4^2$	2,732	6.27	7.48	0.00	72.76
$WT5^2$	2,732	4.90	7.48	0.00	61.47

Note: PS1 = corn; PS2 = soybeans.

Table 4. Summary Statistics for Corn

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Both Models					
PF	2,784	405.17	128.81	248.94	761.46
PX	2,784	4.00	0.43	3.09	5.12
BPX	2,784	−0.34	0.38	−1.13	0.67
A	2,784	22.84	24.71	0.20	164.50
Acreage-specific Model					
PS1	2,784	5.25	0.53	4.49	6.25
PS2	2,784	9.44	1.22	7.11	13.57
LA	2,784	22.15	24.10	0.20	142.80
YC	2,784	104.57	31.91	44.60	193.20
YS	2,784	30.28	8.02	13.14	56.40
YM	2,784	63.25	11.75	34.00	101.40
YW	2,784	35.38	5.54	21.60	59.20
$E(WP)$	2,784	28.64	7.27	13.62	45.40
$E(WT)$	2,784	59.56	1.78	54.44	63.52
$E(WP)^2$	2,784	873.13	416.39	185.59	2,060.71
$E(WT)^2$	2,784	3,550.50	211.24	2,963.93	4,034.16
Yield-specific Model					
Y	2,784	108.18	36.73	18.00	207.00
T	2,784	16.95	8.80	1.00	32.00
T^2	2,784	364.80	300.67	1.00	1,024.00
A%	2,784	12.37	10.73	0.10	59.36
WP1	2,784	0.02	1.95	−6.22	9.17
WP2	2,784	0.01	3.04	−7.70	15.27
WP3	2,784	0.23	4.81	−12.67	23.59
WP4	2,784	−0.37	3.59	−12.75	20.30
WT1	2,784	−0.16	3.68	−12.01	8.48
WT2	2,784	0.02	2.66	−10.29	6.00
WT3	2,784	0.13	2.06	−6.85	7.15
WT4	2,784	0.19	2.07	−6.79	6.04
$WP1^2$	2,784	3.80	6.20	0.00	84.16
$WP2^2$	2,784	9.26	15.77	0.00	233.11
$WP3^2$	2,784	23.18	37.58	0.00	556.25
$WP4^2$	2,784	13.04	30.90	0.00	412.13
$WT1^2$	2,784	13.52	16.24	0.00	144.13
$WT2^2$	2,784	7.04	9.64	0.00	105.84
$WT3^2$	2,784	4.26	7.12	0.00	51.17
$WT4^2$	2,784	4.31	5.81	0.00	46.15

Note: PS1 = wheat; PS2 = soybeans.

Table 5. Summary Statistics for Sorghum

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Both Models					
PF	2,796	404.70	128.72	248.94	761.46
PX	2,796	3.50	0.43	2.60	4.62
BPX	2,796	–0.33	0.41	–1.30	0.64
A	2,796	37.36	26.15	0.30	199.00
Acreage-specific Model					
PS1	2,796	5.25	0.53	4.49	6.25
PS2	2,796	9.43	1.22	7.11	13.57
LA	2,796	37.86	26.38	0.90	199.00
YC	2,796	104.46	31.94	44.60	193.20
YS	2,796	30.25	8.02	13.14	56.40
YM	2,796	63.15	11.77	34.00	101.40
YW	2,796	35.35	5.52	21.60	58.40
$E(WP)$	2,796	27.61	6.89	13.35	42.39
$E(WT)$	2,796	62.34	1.79	57.09	66.27
$E(WP)^2$	2,796	809.86	379.75	178.20	1,797.17
$E(WT)^2$	2,796	3,888.92	221.47	3,259.40	4,392.32
Yield-specific Model					
Y	2,796	64.84	18.21	12.00	134.00
T	2,796	16.90	8.80	1.00	32.00
T^2	2,796	362.91	300.30	1.00	1,024.00
A%	2,796	19.67	9.84	0.20	63.04
WP1	2,796	–0.01	2.32	–7.46	10.94
WP2	2,796	0.12	3.94	–9.43	17.98
WP3	2,796	0.09	3.78	–8.59	20.58
WP4	2,796	–0.38	3.59	–12.75	20.30
WT1	2,796	–0.02	2.94	–8.27	6.49
WT2	2,796	0.02	2.30	–8.83	6.30
WT3	2,796	0.24	2.45	–7.14	8.48
WT4	2,796	0.19	2.06	–6.79	6.04
$WP1^2$	2,796	5.40	8.65	0.00	119.66
$WP2^2$	2,796	15.54	26.47	0.00	323.32
$WP3^2$	2,796	14.27	26.81	0.00	423.45
$WP4^2$	2,796	13.05	30.84	0.00	412.13
$WT1^2$	2,796	8.66	9.32	0.00	68.34
$WT2^2$	2,796	5.30	7.25	0.00	77.97
$WT3^2$	2,796	6.03	9.16	0.00	72.00
$WT4^2$	2,796	4.30	5.82	0.00	46.15

Note: PS1 = wheat; PS2 = soybeans.

Table 6. Summary Statistics for Soybeans

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Both Models					
PF	2,764	403.97	127.94	248.94	761.46
PX	2,764	9.43	1.19	7.11	13.57
BPX	2,764	–0.68	0.68	–1.74	1.21
A	2,764	23.69	24.41	0.05	126.50
Acreage-specific Model					
PS1	2,764	5.25	0.53	4.49	6.25
PS2	2,764	4.00	0.43	3.09	5.12
LA	2,764	23.13	24.25	0.05	126.50
YC	2,764	104.21	31.89	44.60	193.20
YS	2,764	30.20	8.01	13.14	56.40
YM	2,764	63.33	11.69	34.60	101.40
YW	2,764	35.38	5.56	21.60	59.20
$E(WP)$	2,764	27.73	6.87	13.35	42.39
$E(WT)$	2,764	62.34	1.79	57.09	66.27
$E(WP)^2$	2,764	816.44	379.07	178.20	1,797.17
$E(WT)^2$	2,764	3,888.85	221.51	3,259.40	4,392.32
Yield-specific Model					
Y	2,764	31.09	10.86	6.90	61.00
T	2,764	16.92	8.77	1.00	32.00
T^2	2,764	363.18	300.09	1.00	1,024.00
A%	2,764	17.69	18.76	0.02	72.22
WP1	2,764	0.00	2.33	–7.46	10.94
WP2	2,764	0.11	3.95	–9.43	17.98
WP3	2,764	0.11	3.79	–8.59	20.58
WP4	2,764	–0.38	3.61	–12.75	20.30
WT1	2,764	–0.02	2.94	–8.27	6.49
WT2	2,764	0.02	2.30	–8.83	6.30
WT3	2,764	0.25	2.45	–7.14	8.48
WT4	2,764	0.19	2.07	–6.79	6.04
$WP1^2$	2,764	5.43	8.68	0.00	119.66
$WP2^2$	2,764	15.60	26.44	0.00	323.32
$WP3^2$	2,764	14.38	26.94	0.00	423.45
$WP4^2$	2,764	13.14	31.01	0.00	412.13
$WT1^2$	2,764	8.63	9.28	0.00	68.34
$WT2^2$	2,764	5.30	7.27	0.00	77.97
$WT3^2$	2,764	6.05	9.18	0.00	72.00
$WT4^2$	2,764	4.30	5.82	0.00	46.15

Note: PS1 = wheat; PS2 = corn.

irrigation is flawed because technologies, the availability of water, and the cost of obtaining water differ geographically, the results do not accurately identify irrigated acres. These time-invariant effects can be quantified through intercept terms. Weather enters the yield response model as the difference between seasonal expectations and actual weather (precipitation and temperature) and should accurately measure the time-variant effect of seasonal weather on yields.

Results

Tables 7 and 8 present the results of regressions for the acreage and yield response models. The models fit actual acreage and yield responses well with R-square values ranging from 0.896 to 0.985 for acreage and 0.399 to 0.753 for yield. Prices are significant determinants of both acreage and yield responses. Despite expected multicollinearity of the price variables, the sorghum acreage model (Table 8) is the only one that has an insignificant own-price variable. This result is not entirely unexpected since sorghum does not have a futures market and the futures price is calculated by comparing local corn and sorghum spot markets. This relationship of corn and sorghum explains the statistically significant negative soybean cross-price; soybeans are often a substitute for both sorghum and corn. The cross-price results differ *a priori* from theoretical substitute goods for corn only in the wheat model.

The difficulty in analyzing many of the cross-prices as strict substitute goods relates to the complex nature of cropping decisions; a particular crop typically is not a strict substitute or complement in production. Double-cropping is common in some portions of Kansas where winter wheat is planted in the same year as spring crops, further increasing the complexity in explaining the relationships of crops in production. Other unaccounted-for attributes such as soil quality and farmer planting preferences complicate interpretations of crop substitutability so direct interpretation coupled with multicollinearity of crop prices likely underlies many of the statistically insignificant cross-prices.

The limited significance of the soybean price in the corn acreage model (Table 7) further demonstrates the complex nature of planting decisions. Higher corn prices lead to a greater number of acres planted to corn and to soybeans because they are commonly used in rotations. While soybeans are used as complements in production for fixing nitrogen, they also compete for acreage as prices of inputs and outputs change. These complex relationships are evident in the yield model. The fertilizer price coefficient is insignificant for soybeans and negative for corn (Table 7). Soybeans require a relatively small amount of fertilizer and can be used as long-term partial substitutes for fertilizers because they fix nitrogen in the soil, making it available in subsequent production seasons. Increases in fertilizer prices thus provide an incentive for producers to plant crops that are less input-intensive regardless of the quality of the soil.

The role of land quality and input use is further evident in the statistically significant own-price coefficients (Table 8) in the yield model. These results, which suggest that prices influence yield responses, follow Houck and Gallagher (1976) and contradict Menz and Pardey (1983). The negative fertilizer price coefficients follow our theoretical expectations related to input prices, including the insignificant coefficient on nitrogen-fixing soybeans. Basis prices appear to significantly impact producer decisions. Own-basis-prices are positive and

Table 7. Acreage Regression Results

	Sorghum			Corn			Soybeans			Wheat		
Variable	**Coefficient**	**t**	**P > t**	**Coefficient**	**t**	**P > t**	**Coefficient**	**t**	**P > t**	**Coefficient**	**t**	**P > t**
PX	0.060	0.14	0.89	1.440	4.61	0.00	1.161	10.02	0.00	1.926	4.37	0.00
PS1	0.075	0.21	0.83	0.075	0.36	0.72	0.177	0.77	0.44	3.944	5.52	0.00
PS2	−1.012	−6.63	0.00	−0.111	−0.96	0.34	−1.217	−3.62	0.00	−0.890	−3.37	0.00
PF	−0.001	−0.53	0.60	0.004	2.75	0.01	0.007	7.26	0.00	−0.041	−15.06	0.00
BPX	0.604	1.22	0.22	2.176	8.05	0.00	−0.465	−2.93	0.00	4.172	12.75	0.00
LA	0.748	31.19	0.00	0.925	47.43	0.00	0.785	37.65	0.00	0.545	23.99	0.00
YC	−0.124	−7.13	0.00	0.055	5.54	0.00	−0.017	−2.10	0.04	−0.085	−4.08	0.00
YS	0.119	2.37	0.02	0.078	2.13	0.03	0.118	4.72	0.00	−0.269	−4.09	0.00
YM	−0.009	−0.33	0.74	−0.001	−0.04	0.97	0.103	7.34	0.00	0.005	0.15	0.88
YW	−0.072	−1.59	0.11	−0.085	−2.56	0.01	−0.029	−1.07	0.28	0.351	5.29	0.00
$E(WP)$	1.172	1.80	0.07	−0.237	−0.56	0.58	−0.775	−2.93	0.00	−1.744	−3.76	0.00
$E(WT)$	−2.376	−0.49	0.62	−1.640	−0.51	0.61	−1.782	−0.63	0.53	−21.601	−1.31	0.19
$E(WP)^2$	−0.017	−1.73	0.08	0.005	0.75	0.45	0.015	3.15	0.00	0.020	3.51	0.00
$E(WT)^2$	0.018	0.47	0.64	0.014	0.51	0.61	0.014	0.62	0.53	0.198	1.36	0.17
Constant	89.131	0.59	0.55	42.816	0.45	0.66	52.570	0.60	0.55	675.922	1.44	0.15
R-Square		0.8958			0.9642			0.9653			0.9846	
Adjusted R-Square		0.8912			0.9626			0.9638			0.9839	
F Statistic		291.68			517.48			404.23			254.02	
Observations		2,796			2,784			2,764			2,732	

Note: (PS1, PS2) = Wheat (corn, soybeans); Corn (wheat, soybeans); Sorghum (wheat, soybeans); Soybeans (wheat, corn).

Table 8. Yield Regression Results

	Soybeans			Corn			Sorghum			Wheat		
Variable	Coefficient	t	P > t	Coefficient	t	P > t	Coefficient	t	P > t	Coefficient	t	P > t
T	0.926	14.20	0.00	2.393	12.08	0.00	1.828	13.38	0.00	0.509	5.10	0.00
T^2	−0.016	−7.47	0.00	−0.034	−5.09	0.00	−0.037	−7.91	0.00	−0.006	−1.56	0.12
PF	0.002	1.13	0.26	−0.017	−3.58	0.00	−0.009	−2.55	0.01	−0.005	−1.90	0.06
PX	0.780	6.30	0.00	4.858	5.02	0.00	6.640	9.28	0.00	3.566	12.33	0.00
BPX	0.629	2.94	0.00	10.449	9.57	0.00	1.423	1.89	0.06	−0.310	−1.01	0.31
A	−0.021	−1.15	0.25	−0.271	−4.77	0.00	−0.035	−0.99	0.32	−0.040	−3.09	0.00
A%	−0.044	−1.64	0.10	0.739	5.37	0.00	0.065	0.84	0.40	0.187	5.30	0.00
WP1	0.056	0.87	0.39	0.442	2.00	0.05	0.629	4.57	0.00	−0.193	−3.32	0.00
WP2	0.185	5.43	0.00	−0.330	−2.36	0.02	0.446	5.67	0.00	0.396	5.83	0.00
WP3	1.006	25.02	0.00	1.766	20.87	0.00	2.241	27.16	0.00	0.196	2.28	0.02
WP4	0.408	11.17	0.00	0.767	6.71	0.00	0.549	6.90	0.00	−0.433	−7.46	0.00
WP5	—	—	—	—	—	—	—	—	—	−0.589	−10.63	0.00
WT1	0.182	1.96	0.05	−0.469	−1.97	0.05	−0.111	−0.61	0.54	0.039	0.47	0.64
WT2	−0.036	−0.29	0.78	−0.370	−1.23	0.22	0.529	2.13	0.03	0.189	2.20	0.03
WT3	−0.130	−1.14	0.26	0.919	2.72	0.01	−0.228	−0.96	0.34	−0.362	−5.94	0.00

Continued on following page

Table 8. (continued)

Variable	Sorghum			Corn			Soybeans			Wheat		
	Coefficient	t	P > t	Coefficient	t	P > t	Coefficient	t	P > t	Coefficient	t	P > t
WT4	−0.002	−0.02	0.99	−0.602	−1.64	0.10	0.590	2.31	0.02	−0.541	−7.71	0.00
WT5	—	—	—	—	—	—	—	—	—	−0.240	−2.37	0.02
$WP1^2$	−0.047	−2.56	0.01	0.022	0.30	0.77	−0.085	−2.27	0.02	0.010	1.68	0.09
$WP2^2$	−0.012	−2.60	0.01	−0.058	−2.38	0.02	−0.067	−5.86	0.00	−0.037	−5.24	0.00
$WP3^2$	−0.076	−12.80	0.00	−0.146	−13.53	0.00	−0.199	−13.02	0.00	−0.039	−2.23	0.03
$WP4^2$	−0.033	−8.37	0.00	−0.060	−4.83	0.00	−0.040	−5.42	0.00	−0.084	−7.08	0.00
$WP5^2$	—	—	—	—	—	—	—	—	—	0.016	2.27	0.02
$WT1^2$	−0.006	−0.33	0.74	0.062	1.66	0.10	0.032	0.78	0.43	−0.126	−7.42	0.00
$WT2^2$	0.028	1.04	0.30	0.091	1.50	0.13	0.041	0.70	0.48	0.141	4.63	0.00
$WT3^2$	0.001	0.06	0.95	0.041	0.53	0.60	0.090	2.10	0.04	0.015	0.91	0.36
$WT4^2$	−0.002	−0.08	0.94	−0.220	−2.46	0.01	0.063	0.96	0.34	−0.159	−6.87	0.00
$WT5^2$	—	—	—	—	—	—	—	—	—	−0.197	−8.23	0.00
Constant	16.627	11.60	0.00	71.534	14.93	0.00	31.438	8.73	0.00	10.648	3.91	0.00
R–Square		0.6724			0.7531			0.4866			0.3999	
Adjusted R-Square		0.6567			0.7414			0.4623			0.3699	
F Statistic		106.98			81.6			74.05			49.37	
Observations		2,764			2,784			2,796			2,732	

Note: (PS1, PS2) = Wheat (corn, soybeans); Corn (wheat, soybeans); Sorghum (wheat, soybeans); Soybeans (wheat, corn).

statistically significant for most of the acreage and yield models. The only exceptions are wheat yields and soybean/sorghum acres; those coefficients are statistically insignificant and/or relatively small. The outcomes suggest that producer perceptions of future harvest prices are based on more than forward contracts, which confirms the need for further analysis of those perceptions. The analysis of basis prices in the acreage and yield models shows that a $0.50 basis price would increase per-county production of corn by 5,683 bushels and a $1.00 basis price would increase per-county production by 22,733 bushels. Although these production shifts seem relatively small, on a national scale the impact would be large and significant.

The significance of the lagged acreage variable is expected because it measures producers' inability or unwillingness to respond to price changes due to a variety of factors, including their capital purchases and preferences. On a less aggregated scale, the lagged acreage variable can be used to quantify crop rotations and has been shown to be negative for select crops (Hendricks 2011). However, at aggregate levels, such measurements of site-specific characteristics and cropping patterns are unobservable. At the county level, the lagged dependent variables measure general trends within agriculture. According to our results, corn acreages are adjusted more slowly to the long-run equilibrium than wheat acreages. The large coefficient for corn is likely due to increases in direct payments and other government programs, which have shifted simple price incentives.

Inclusion of acres in the yield models resulted in statistically significant coefficients for corn and wheat yields. The positive coefficient on percent acreage ($A\%$) for both corn and wheat illustrates the comparative advantage of production of these crops within counties. The negative coefficient for the acreage variable (A) demonstrates that increases in production on the extensive margin have a negative impact on yields. Recent expansions of corn production in Kansas to land that is marginal in quality have negatively impacted aggregate yields with important consequences for the supply response, and policymakers and agribusinesses must understand those impacts.

This result emphasizes the importance of understanding the relationship between aggregate acres planted and yields in commodity supply. Assumption of a homogeneous yield response despite an expansion of acres planted will overestimate the supply response. Furthermore, the process of bringing lower-quality land into production of an input-intensive crop can have negative environmental consequences related to more extensive applications of water and/or fertilizer. Thus, expansion of production to marginal acres will continue to play a large role in agricultural supplies and environmental outcomes.

Further evidence of the relationship between acres planted and yields is shown in Table 9. Soybeans have the greatest short-run total supply elasticity, followed by wheat, corn, and sorghum. Corn and soybeans have the greatest own-price acreage elasticity because they are highly substitutable in production. Our results for corn and soybeans are similar to those of Lin and Dismukes (2007). However, our results for wheat more closely follow Huang and Khanna (2010), which found a limited acreage response for the winter crop. Corn has the smallest own-price yield elasticity. Since the own-price yield elasticity captures both increases in inputs and soil quality, the only response to an increase in corn yields is to increase use of inputs (fertilizer) because corn is already planted on the most productive land. Sorghum and wheat, on the other hand, are planted on inferior land, and increases in their prices should

Table 9. Total Crop Supply Elasticities

	$\varepsilon_{A,PX}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PX}$	$\varepsilon_{SR\ TS,PX}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PX}$
	Acreage, Output Own-price	Yield, Acreage	Yield, Output Own-price	Short-run Supply, Output Own-price	Acreage, Lagged Acreage	Long-run Supply, Output Own-price
Wheat	0.096	–0.118	0.526	0.611	0.550	0.714
Corn	0.252	–0.057	0.180	0.417	0.897	2.484
Soybeans	0.462	–0.016	0.237	0.691	0.767	2.183
Sorghum	0.006	–0.020	0.358	0.364	0.758	0.381
	$\varepsilon_{A,PF}$	$\varepsilon_{Y,A}$	$\varepsilon_{Y,PF}$	$\varepsilon_{SR\ TS,PF}$	$\varepsilon_{A,LA}$	$\varepsilon_{LR\ TS,PF}$
	Acreage, Input Price	Yield, Acreage	Yield, Input Price	Short-run Supply, Input Price	Acreage, Lagged Acreage	Long-run Supply, Input Price
Wheat	–0.147	–0.118	–0.053	–0.183	0.550	–0.341
Corn	0.066	–0.057	–0.064	–0.002	0.897	0.537
Soybeans	0.128	–0.016	0.026	0.152	0.767	0.564
Sorghum	–0.012	–0.020	–0.056	–0.068	0.758	–0.104

Notes: Elasticities for [model], [variable of interest] per equations 3 through 5. The input price is the cost of fertilizer.

increase the quality of land to which those crops are planted, replacing corn on moderate-quality plots. Thus the own-price yield elasticity is greatest for crops other than corn.

The expansion to marginal acres decreases the total supply elasticity for corn by 3.5 percent. The supply elasticities for soybeans, wheat, and sorghum decrease by 1.1 percent, 1.9 percent, and less than 1 percent respectively. This result is important since policies that encourage production on marginal acres will also reduce average yields, information that is useful to supply forecasters and insurers.

The elasticity results demonstrate the importance of analyzing the responses of both acreage and yield. Omission of one portion of supply will underestimate the total response. Individual acreage and yield elasticities are significantly smaller than elasticities for the combined total supply, a result that becomes increasingly evident in the long-run elasticities. Because the lagged acreage variable measures the impact of production decisions on acreage planted in subsequent seasons, the lagged acreage elasticity affects other acreage-related elasticities. Wheat and sorghum, for example, have relatively small acreage response elasticities so their long-run elasticities are relatively less affected by the lagged acreage elasticities.

Although some of the long-run supply elasticities in our results fall outside of the bounds predicted by traditional production theory when inelasticity of supply prices is assumed, the results provide insight into producer behavior and general trends. Our elasticity results generally are similar to the long-run supply elasticities found in other studies (Nerlove and Addison 1958). The long-run elasticities also show the additive or multiplicative effect of various policies directly and indirectly on commodity supply. Policies that encourage the conversion of land to specific crops have direct negative effects on average yields for multiple years that are captured in the lagged acreage elasticity.

The short-run supply response elasticities with respect to fertilizer prices are negative for wheat, corn, and sorghum and positive for soybeans. The positive own-price acreage elasticity for corn is unexpected because it is an input-intensive crop. However, the strong correlation of prices for corn, fertilizer, and oil likely is attributable to the positive marginal coefficient for fertilizer. The largest yield elasticity with respect to fertilizer price is for corn and is related to corn's intensive use of inputs, especially when not produced in a rotation. The positive soybean elasticity further shows the complex relationships involved in producers' planting decisions since soybeans are often planted as an alternative to more input-intensive crops and as a long-run substitute for fertilizers.

Our results show that both climate and weather impact acres planted and yields. The influence of climate on acreage decisions is significant for soybeans and wheat. Greater precipitation decreases wheat acres planted, and the largest number of sorghum acres is planted at approximately 34 inches of total rainfall. Temperature is not a significant determinant of acres planted for any of the crops. This is likely due to correlation and multicollinearity between precipitation and temperature for many counties.

The impact of weather on yields varies by crop, and the level of statistical significance of precipitation's impact on yields is greater than that of temperature. Only two of the thirty-four precipitation variables are insignificant at a 90 percent confidence interval while half of the temperature variables are significant. The amount of precipitation received in the period between planting and harvesting of corn, sorghum, and soybeans significantly impacts yields. Yield-maximizing levels of rain in excess of expected precipitation during that period are 6.06 inches for corn, 5.63 inches for sorghum, and 6.65 inches for soybeans. Furthermore, those spring crops have greater yields in response to modest increases in precipitation for all of the production periods.[9] Wheat yields are negatively impacted by increases in precipitation in later periods of growth and harvest since those grains must dry out prior to being harvested.

Conclusion

A greater understanding of producers' land use and supply decisions is imperative if the agricultural industry is to continue to move forward. Given recent changes in the nation's climate and in commodity markets, grain producers and processors would benefit significantly from a more comprehensive ability to estimate future supplies for hedging and production decisions. Our results point to an intricate relationship between acres planted and yields, two important components of supply responses. The models in this study estimate acreage decisions and yields for the four major field crops in Kansas and demonstrate that producers' land use decisions are sensitive to both weather and prices. The combined elasticity method we present more accurately estimates supply responses because it captures both traditional acreage and yield responses plus the impacts of increasing production on the extensive margin. Kansas producers have planted record numbers of acres to various grains in recent years, and traditional methods, which have ignored

[9] Modest decreases in precipitation during the planting stage increase yields of corn. In the other eleven stages, corn yields increase only when precipitation is greater than normal.

production on the extensive margin, have overestimated supply responses. We show that using own-price acreage elasticities underestimates the supply response by between 33 percent and 98 percent and using own-price yield elasticities underestimates total response by between 2 percent and 66 percent. These results clearly demonstrate the importance of combining acreage and yield responses.

Another goal of this study was to develop a new method by which to estimate producer price expectations with lagged basis prices. The results show strong statistical significance of the impacts of lagged basis prices on subsequent production decisions. In an efficient futures market, we expect long-run basis prices to average toward zero or a premium/discount, but short-run deviations influence inter-seasonal supply decisions. Relative to using futures prices only, using the marginal impacts of basis and futures prices more accurately accounts for producer perceptions of futures markets. Future studies could compare the ability of different methods that incorporate basis prices and various weighting strategies to accurately measure producer price expectations.

Agricultural markets in the United States have undergone rapid changes in recent years, and a renewed understanding of supply responses is warranted. Both climate change and increasing global demand for agricultural commodities will push producers to expand production to marginal acreage, which will inevitably impact the environment and our understanding of supply responses. Future research to estimate impacts of climate change and intra-seasonal weather fluctuations on yield and acreage responses would be useful. And as production expands to less productive acres, the sensitivity and responsiveness of crops to weather is likely to vary. Advancing our understanding of these factors and quantifying producers' expectations related to production and prices are critical when analyzing and measuring a supply response.

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