Is Yield Endogenous to Price? An Empirical Evaluation of Inter– and Intra–Seasonal Corn Yield Response *

Barry K. Goodwin, Michele Marra,
Nicholas Piggott and Steffen Müeller

June 3, 2012

Abstract

An extensive empirical literature has examined the behavior of crop yields over time. Corn yields have been characterized by significant increases reflecting an array of technological developments that have substantially boosted productivity. While much of the focus has been on modeling deterministic and possibly stochastic trends in yields over time, an equally important question involves the extent to which yield changes may occur in response to price. This paper addresses two dimensions of this issue. We first look at the extent to which realized yields (i.e., at harvest) tend to be influenced by planting–time quotes of post–harvest futures contracts. Second, we examine the potential for intra–seasonal responsiveness of yields to significant price swings. The latter response is especially important in light of recent arguments that weather offers identification through instruments that are completely exogenous to market conditions—a view often expressed in terms of a "natural experiment." We challenge this argument by finding that the potential does exist for yields to be affected by significant price changes that occur early in the growing season.

* This work was supported by the Iowa Corn Promotion Board and by Monsanto. Goodwin is William Neal Reynolds Distinguished Professor in the Departments of Economics and Agricultural and Resource Economics Departments at North Carolina State University. Marra and Piggott are professors in the Agricultural and Resource Economics Department at North Carolina State University. Müeller is Principal Research Economist for the Energy Resources Center at the University of Illinois at Chicago. Direct correspondence to Goodwin at Box 8109, North Carolina State University, Raleigh, NC, 27695, E-mail: barry_goodwin@ncsu.edu.

Is Yield Endogenous to Price? An Empirical Evaluation of Inter– and Intra–Seasonal Corn Yield Response

1 Introduction

An extensive empirical literature has examined the behavior of crop yields over time. Corn yields have been characterized by significant increases reflecting an array of technological developments that have substantially boosted productivity. While much of the focus has been on modeling deterministic and possibly stochastic trends in yields over time, an equally important question involves the extent to which yield changes may occur in response to price changes. This paper addresses two dimensions of this issue. We first look at the extent to which realized yields (i.e. at harvest) tend to be influenced by planting-time quotes of post-harvest futures contracts. Second, we examine the potential for intra-seasonal responsiveness of yields to significant price changes. The examination of the role of price on yields is motivated by the recent unprecedented increase in price volatility in the U.S. corn market and, in particular, the role price plays in signaling market responses to the current demand and supply situation and the bidding of acreage away from other crops, thereby increasing supply. The implications of our analysis are directly pertinent to an ongoing exchange over structural identification in empirical models of supply. Further, our results are relevant to the ongoing debate over bioenergy policies and their implications for land use. In particular, the extent to which the high corn prices that have been triggered by ethanol policies impact land use decisions is critically dependent upon how yields respond to prices

Although agricultural supply models have been dominated by models of acreage response to price movements, yields have been historically assumed to respond to exogenous weather and technology variables (Shaw and Durost 1965, Schlenker and Roberts 2006, 2009, Deschenes and Greenstone 2007, Tannura, Irwin, and Good 2008)), there is a body of literature that supports significant responsiveness of crop yields to economic factors such as input and output prices. Houck and Gallagher (1976) estimate corn yields as a function of one-year-lagged fertilizer-to-corn price ratio, corn acreage, a weather variable and a technology trend for the 1951-1971 period, and find corn price yield elasticities in the range of 0.25 - 0.75.[1] Menz and Pardey (1983) re-estimate Houck and Gallagher's (1976) equation for the 1972-1980 period and find no significant price-yield response, noting that for the latter period, not only annual increments in nitrogen application were smaller, but also the marginal product of nitrogen was smaller, resulting in less price responsiveness. Choi and Helmberger (1993) investigate the sensitivity of various crop yields to prices using time series from 1964-1988. They use a recursive system in which they first estimate fertilizer use as a function of producer and fertilizer prices and idle acreage, and then estimate a yield equation as a function of fertilizer use, planted acreage, and weather. They estimate a corn price-yield elasticity of 0.27, but note this should be considered an upper-bound elasticity, since it becomes null when including a time trend to account for technology.

Huang and Khanna (2010) is perhaps the most recent study incorporating prices in the yield equation, while taking price endogeneity into account. Using Choi and Helmberger's reduced-form specification of crop yields, they estimate a panel data, instrumental variable (IV), fixed effects model of crop yields as a function of climate variables, lagged crop and fertilizer prices, practice measures, and measures of intensive and extensive cropland expansion. They use county yield data for the period 1977-2007. Lagged precipitation, growing degree days, state-level crop stocks, and crop price and yield risks are used as instrumental variables for prices and other endogenous variables in the yield equation.[2] The authors find a statistically significant corn price-yield elasticity of 0.15.

Most existing studies of agricultural yields use OLS as the main econometric method for estimation and generally assume a linear or quadratic time trend. Nelson and Preckel (1989) propose a conditional beta distribution as a parametric model of the probability

[1]The authors point out the weakness of their weather variables, as well as possible room for improvement with regards to their price expectation (one-year lagged prices), which they argue implies the simplest form of price-expectation formation. Similarly, the fertilizer price data is an aggregate index averaged over the previous crop year.

[2]Intensive land expansion refers to expansion to crop acreage previously planted to other crops, while extensive land expansion refers to expansion on previously idle or non-cropland acres.

distribution of agricultural output. The authors condition yield distributions as a function of a vector of inputs by expressing the distribution parameters as a function of inputs. They measure and report elasticities of mean, variance, and skewness measures with respect to fertilizer application of nitrogen, phosphate, and potassium. Ervin et al. (2010) provide a comprehensive assessment on the effects of GM crops on U.S. farm income, agronomic practices, production decisions, environmental resources, and personal well-being. The study finds that genetic-engineering technology has produced substantial net environmental and economic benefits to U.S. farmers. As corn prices rise, the derived demand for the new, significantly higher yielding corn hybrids will also increase, thus providing an additional linkage between corn price and yield.

Various theoretical models and empirical evidence support a significant responsiveness of crop yields to prices. For instance, Hayami and Ruttan (1985) formalized and empirically verified their induced innovation hypothesis that links the emergence of innovation with economic conditions. According to the induced innovation hypothesis, food shortages or high prices of agricultural commodities are likely to lead to the introduction of new high-yielding varieties. Further, the work of Boserup (1965) and Binswanger and McIntire (1987) on the evolution of agricultural systems support the induced-innovation hypothesis (Sunding and Zilberman, 2001). Price induced technology adoption is supported in Griliches (1957) seminal study, where he finds that all parameters of a technology diffusion logistic function (diffusion at start of estimation period, long-run upper limit of diffusion, and pace of diffusion) are largely affected by profitability and other economic variables, which are direct functions of output prices.

Thus, besides price-induced innovation, profit maximizing behavior of farmers with respect to input decisions at planting time and within the growing season are affected by farmer's expectations of corn prices at harvest time. As Just and Pope (2011) state *"each time a crop is planted, a producer can choose to grow a different crop, use a different seed variety, apply fertilizer, use herbicides, apply insecticides, or employ plant-growth regulators"* (p. 643). Importantly, the set of input choices available to farmers has dramatically changed since the introduction and widespread adoption of genetically modified corn, which reached an 80% acreage share in the U.S. Central Corn Belt in 2009. In addition to the seeds planted being genetically modified with yield enhancing and risk reducing traits, the refuge requirements have also transformed such that adopters of the most recent trait technologies are afforded smaller refuges. This transformation means more of the genetically modified seed is being planted than previously, leading to higher average yields being achieved. This should be factored into the calculation of the price-yield elasticity.

In summary, although crop yields have been historically modeled as a function of non-economic factors, such as weather and technology representations, a body of literature supports a positive and significant, though inelastic, response of crop yields with respect to prices. However, this existing literature uses very old time series data as well as econometric techniques that do not take price endogeneity into consideration. Most studies also rely on inappropriate distributional assumptions of crop yields or yield trends. Further, none of the previous measures of price-yield elasticity has taken into account the current agricultural economic environment with a wider set of genetically engineered crop seed varieties, the transformation of refuge requirements for the more recent trait technologies, and associated optimal agronomic and managerial practices.

2 The Identification Conundrum

A recent strand of empirical research has argued that the measurement of price impacts on market relationships are nearly always endogenous, thereby damning a large body of existing research. The argument insists that identification can only be achieved in cases of a "natural experiment" or when nature dictates that an identifying instrument is truly exogenous. While arguments in favor of the need for exogenous instruments are unassailable, the specific instruments applied by advocates of this approach may not always offer advantages over the alternatives that they so readily criticize.

Roberts and Schlenker (2011) argue that traditional approaches to identification (e.g., Nerlove (1958)) in models of supply suffer from endogeneity biases because prices are endogenous to market-anticipated supply shocks. They propose weather shocks as a natural candidate for identification, arguing that weather and the resultant shocks to yield are purely exogenous to market conditions. While arguments regarding the exogeneity of weather shocks certainly seem valid, the implicit assumption that the effects of weather shocks on yield (and therefore supply) are exogenous may be open to debate. In particular, to the extent that yields are endogenous to changes in market conditions during the growing season, weather shocks may not offer an exogenous approach to identification. Put differently, while weather shocks may be exogenous, if producers react to weather shocks in a manner that is endogenous to market conditions during the growing season, their impacts on yields are not.

3 The Bioenergy-Land Use Debate

Rising oil prices, uncertain oil sources and possible environmental gains of renewable fuels have led to policy-driven mandatory increases of ethanol production. A new mandate for up to 7.5 billion gallons of "renewable fuel" to be used in gasoline by 2012 was included in the Energy Policy Act of 2005 (Farrel et al, 2006). Further, the 2007 Energy Independence and Security Act of 2007, or CLEAN Energy Act, mandates an increase of ethanol production from 4.7 billion gallons in 2007 to 15.2 billion gallons in 2012 to 36 billion gallons in 2022 (U.S.GPO, 2007).[3]

Searchinger et al. (2008) is perhaps the first study to point out that while the majority of studies analyzing greenhouse gas (GHG) emissions of biofuels compared to those of fossil fuels rely on the fact that growing biofuel feedstock removes carbon dioxide from the atmosphere, and thus reduce GHG, (sequestration effect or feedstock carbon uptake credit), they do not take into account the carbon costs, carbon storage, and sequestration sacrificed by diverting land from their existing uses. Further, Fargione et al. (2008) observe that converting native

[3]The Act further specifies that 21 billion gallons must be derived from non-cornstarch products, such as sugar and cellulose.

habitats to crop land releases CO2 as a result of burning or microbial decomposition of organic carbon stored in biomass and soil. They define a "biofuel carbon debt" as the first 50-year period of CO2 emissions caused by ethanol-triggered land conversion. The authors argue that rising grain prices would cause a substantial portion of the acreage currently enrolled in the U.S. Conservation Reserve Program be converted to cropland. Further, they estimate that ethanol from corn produced on newly converted U.S. central grassland results in a biofuel carbon debt repayment time of 93 years. Overall, they conclude that converting rainforest, peat lands, savannas, and grassland to produce crop based biofuels in Brazil, Southeast Asia, and the United States creates a "biofuel carbon debt" by releasing 17 to 420 times more CO2 than the annual GHG reductions that these biofuels would provide by displacing fossil fuels. It is argued that until the carbon debt is repaid, biofuels from converted lands have greater GHG impacts than those of the fossil fuels they displaced.

Some studies go even further to state that the indirect land use effects completely outweigh the carbon savings from some biofuels, relative to petroleum products (Laborde, 2011; Hertel, et al. 2010), which implies that the carbon debt would never be repaid. It is difficult to compare the studies because they use different data sets, different modeling approaches, and different assumptions in their models, but it seems unlikely that either extreme (not considering ILU effects at all or assuming they completely outweigh the gains from biofuels) is plausible.[4]

The California Low Carbon Fuel Standard (LCFS) and the Renewable Fuels Standard (RFS2) are sets of criteria (state and Federal, respectively) that take account of the effect of the production of various types of renewable fuels, such as corn-based ethanol, on changes in land use and those changes' effects on the environment, especially the carbon cycle. The Global Trade Analysis Project (GTAP) model and similar computable general equilibrium models are used to predict land use change in response to higher demand for ethanol. The

[4] Although beyond the scope of this study, the extent to which double cropping has mitigated potential increases in acreage use is a factor that has not been addressed in any systematic manner, at least to our knowledge.

accuracy of the output of this and other computer models depends on empirical inputs concerning agricultural input use and output responses to input and output prices. Particularly, estimated changes in land use triggered by higher corn demand are highly sensitive to the price-yield elasticity parameter used in GTAP runs.

As part of his participation on the Expert Working Group for the California Low Carbon Fuel Standard development, Berry (2011) provides a critical review of the current price yield elasticity literature. Berry's general view of the literature is expressed as follows (page 8): "However, there is a literature that attempts to estimate the price elasticity of yield. Unfortunately, most of this literature is quite bad." One of the papers critically reviewed by Berry is a 2009 publication by Keeney and Hertel, which relies on Houck and Gallagher, Menz and Pardey, and Choi and Helmberger to form the intellectual basis for the inclusion of a corn price-yield elasticity of 0.25 assumed in the GTAP model.

Berry argues that GTAP relies on a misleading reading of the empirical literature regarding price-yield elasticities and that the assumed price-yield elasticity parameter is erroneous. He argues that studies estimating significant price-yield elasticity parameters are not only based on outdated time series data (1951-1988), but also utilize inappropriate econometric techniques (OLS), which ignore the simultaneous equation bias implicit in the estimation of supply equations. Berry favors two recent studies of yields providing evidence of a price-yield elasticity ranging from 0.0 (Roberts and Schlenker) to 0.15 (Huang and Khanna).

4 The Timing of Production Decisions

While researchers often profess an ability to adequately apply an econometric model to represent the actions of economic agents, they are also often guilty of ignoring basic institutional details that can be gleaned from a simple discussion with farmers. To this end, an important component of this research effort involved a "focus–group" type of meeting with growers and seed dealers.[5] Producers and those with direct interest in the timing of production were queried about the timing of their input decisions.

Figure 1 below presents a table derived from their responses. An important fact is revealed from the table of results—farmers often undertake actions that will likely impact their realized yield after planting. Notable is the fact that nitrogen application occurs in March and April and side–dressing and the application of chemical inputs continues through June. It is also relevant to note that longer-run production decisions such as the purchase of seeds and fertilizer may occur in the fall months that preceded planting. Finally, it is relevant to note that long–term, multi–year decisions such as the purchase of new farm equipment or irrigation systems may occur over multiple years.

5 Empirical Results

The goal of our empirical analysis is to assess the extent to which yields may be responsive to price changes. There are several important dimensions to this issue. First, as the relative price of a commodity changes from season to season, one anticipates that producers will alter their production by planting different crops or otherwise adjusting productive inputs. As the focus group results indicated, farmers may choose to purchase new farm equipment or otherwise make significant capital investments over a multi–year period. We focus on corn production decisions in a relatively homogeneous region of the Corn Belt that is comprised of Iowa, Indiana, and Illinois—collectively known as the "I-States." Technological change has had an overwhelming influence on crop yields in recent years. Any model of yields must formally address yield trends though the modeling of such trends can be a challenging exercise in and of itself. We focus on the modern period of production that has occurred since the introduction of biotechnolgy for corn—1996-2010. Although our models formally include parametric and non-parametric representations of yield trend, changes in production practices over time lead us to focus on this recent period rather than to consider yield and

[5] This focus group was held on January 18, 2012 in Johnston, Iowa and included five Iowa corn growers, representatives from the Iowa Corn Growers' Association, and representatives of Monsanto.

production relationships prior to 1996. It is important to also note that farm policy realized significant structural changes with the 1996 FAIR Act. The flexibility in production afforded to producers under this legislation would be expected to affect production decisions. This reinforces our focus on yield behavior since 1996.

Crop yields for the three "I-States" were collected from the USDA's National Agricultural Statistics Service sources. We use the NASS reported yields at the crop–reporting district level.[6] Our focus on crop reporting districts is made to conform most closely to the definition of climate zones, as we discuss below. First and foremost, we are interested in evaluating the inter– and intra–seasonal impacts of price changes on yields. The existing research has produced yield/price elasticity estimates that range from 0.0 to 0.25. To our knowledge, no existing research has explicitly addressed the potential for yields to change in response to price within the growing season.

Of course, realized yields will be significantly affected by environmental conditions at planting and over the growing season. Considerable recent attention has been directed toward the relationships between corn yields and such environmental factors as precipitation, soil moisture, and temperature. Schlenker and Roberts (2010) find important nonlinear and threshold impacts of temperature on yields. A variety of different metrics representing weather conditions are available. On the basis of anecdotal evidence as well as published research, we choose two specific measures of growing conditions—average temperature and Palmer's Z–index. Our data were collected from the National Climate Data Center. Palmer's Z drought index represents a normalized measure of soil moisture relative to a normal state. Thus, high positive values indicate a surplus of moisture while negative values represent a moisture deficit. These data are available on a monthly average for climate zones, which are defined as a grouping of counties that are expected to have relatively homogeneous weather conditions. The specific definition of a climate zone is not the same as that of crop reporting districts. Thus, to construct CRD measures of weather conditions, we used the climate

[6] NASS typically reports yields on a harvested–acre basis. We repeated our analysis for planted acre yields and obtained qualitatively identical results. The issues of abandonment and silage production complicate the measurement of yield. However, this distinction did not seem to have important impacts in our analysis.

zone metrics for each county and then aggregated county data to obtain CRD–level weather variables. The CRD–level weather variables were given as harvested-acre weighted averages across all counties in the district.

The average of the closing price for all trading days in February for post–harvest contracts (November for soybeans and December for corn) were used to represent expected prices. We also constructed a measure of intra–seasonal price movements by considering the ratio of the April and February prices for the post–harvest contracts. In logarithmic form, this represents the percentage change between April and February for the futures contract. This is intended to measure intra–season price movements. We also included a non–parametric time trend (using the generalized additive models discussed below) and a measure of the adoption of biotech varieties having insect–resistant traits. The biotech adoption statistics were only available at the state level and thus were constrained to be the same for a given year for all districts in a state.[7] Adoption of biotech corn hybrids is illustrated below in Figure 2. Fertilizer prices were collected from the *Economic Report of the President*. Price variables were deflated by the consumer price index. Table 1 contains variable definitions and summary statistics.

All of our models contain CRD–specific fixed effects. We first consider a standard OLS specification with fixed effects. The issue of an appropriate price deflator is always pertinent when considering agricultural prices observed over time. Most commonly used deflators—such as the CPI—tend to over–adjust for the effects of deflation. This is because long–run price levels for agricultural commodities have not risen at the same pace as the overall cost of living. One way to address this problem is to consider relative prices. To this end, we test whether the real price effects of corn and soybeans are of equal magnitude but of opposite sign. We confirm that indeed this hypothesis is not rejected (with an associated F-statistic of 0.21) and thus for the remainder of our models we consider the logarithm of the ratio of

[7] Prior to 2000, biotech adoption statistics are only available at a national level. The ratio of each state's adoption to overall adoption was used to scale the national statistics for the years 1996-1999. Note that biotech adoption was quite low in these early years and thus the results were not particularly sensitive to this scaling.

corn to soybean prices as the relevant price variable. Using pooled data for the three states, we estimated yield–response equations.

A third version of our model includes a nonparametric representation of the trend effects common to all CRD units in the panel. We use the backfitting algorithm of Hastie and Tibshirani (1986) with cubic spline function used to represent the nonlinear trend effects. We use spline smoothing to represent the nonlinear trend effects and use the generalized cross validation criterion of Wahaba (1990) to determine the bandwidth parameter used in smoothing. We then estimate this third version of the model independently for each of the three states considered. Parameter estimates for the aggregate models are presented in Table 2 while estimates for the state–specific models are presented in Table 3. An illustrative example of spline trend effects is presented in Figure 3 for each of the Iowa crop reporting districts.

The estimates are largely consistent with prior expectations. We find that a higher Z index in May corresponds to a lower yield while a higher Z index during the summer period of active plant growth (July) corresponds to a significantly higher yield. The results likely reflect the difficulties associated with excessive moisture during planting and drought stress during July.[8] Excessive heat during the July growing season is negatively related to yield. Again, this is in accordance with the impacts of general agronomic conditions that are associated with corn production. The effects are quite similar across all of the aggregate model specifications. Note that the panel nature of our data suggests the potential need for clustering–adjusted standard errors. These are also presented for Model 2. The results demonstrate that such clustering does not have an important impact on the inferences.

Perhaps of greatest interest in the effect of intra–season price movements on yields. The results suggest that a small but statistically–significant response of yields occurs when prices strengthen or fall early in the growing season. The result is statistically significant in every case. For our sample of data taken over the 1996-2010 period, prices tended to increase by

[8]Note that the soil moisture indexes are somewhat backward looking in that they consider soil moisture during a month, which will be influenced by precipitation during prior months. Alternative measures of soil moisture deficiencies that consider variable lags in moisture content are also available but are expected to be highly correlated with Palmer's Z index.

about 1% on average between February and April. At the average yield value for 2010, our results suggest that if prices rose by 2% instead of 1% (i.e., a 100% increase in the rate of price increase between February and April), yields would be approximately 0.6-1.0% higher than if the usual price change of 1% were to be observed.

Table 4 presents price elasticity estimates for all six models considered. In general, the aggregate models suggest a long-run price–yield elasticity of about 0.19-0.27, which is consistent with the 0.25 estimate currently used in the GTAP modeling framework. The results are quite similar to the survey of existing elasticity estimates presented elsewhere in the literature. Again, at the average price change and yield levels, intra–seasonal price elasticities of about 0.006-.0108 are revealed, suggesting a modest but statistically significant intra–seasonal response of yields to price changes. The long–run price–yield elasticities range from 0.15 to 0.43 at the state–level. In that these states make up a significant proportion of total corn production in the US, these results may suggest adopting a relatively more elastic yield response to price when modeling land use and other economic factors in general equilibrium models.

Evidence gleaned from a review of the literature as well as the focus group discussions with Iowa farmers suggested that fertilizer application during the early part of the growing season may be an important mechanism by which realized yields may be affected by intra-seasonal price changes. To examine the extent to which fertilizer demand appeared to be sensitive to price, we collected fertilizer usage data and relevant variables for the 1964-2009 period. Fertilizer usage is represented in terms of the total uptake by corn divided by planted corn acreage. The relative price of nitrogen is given by the ratio of the ammonia price to the corn price. Parameter estimates and relevant statistics are presented in Table 5. The estimates confirm a positive and statistically significant relationship between fertilizer application and intra–seasonal price changes. Statistically significant impacts on nitrogen use in response to price changes between February and April are confirmed. Again, this result suggests that producers' self-protection and crop management practices may differ according to changes in market conditions early in the growing season. This confirms one possible avenue by which the impacts of weather shocks on yields may be endogenous to price.[9]

6 Summary and Conclusions

This paper reports on an investigation of the relationship between yields and relevant economic factors, including prices. We find that year–to–year price changes tend to correspond to acreage adjustments that are similar to those commonly reported in the literature. In particular, a long–run elasticity of about 0.25 exists for the yield response to prices. We also find that yields respond in a very small but statistically significant way to changes in prices during the growing season, represented here as the February to April period. At the mean values, if the percentage rate of change in prices rose from its average value of 1% to 2%, yields would increase by about 0.1%. These results are consistent with focus group discussions that suggested the potential for intra–seasonal adjustments that would increase realized yields. These results may have important implications for the ongoing debate over structural identification of price impacts. In particular, if the potential for adjusting input usage and production practices exists during the growing season and after planting, the effects of market–level structural shocks such as weather may actually be endogenous to prices. Put differently, if yields adjust to intra–seasonal price changes, agents may react differently to weather shocks when prices are rising than is the case when prices are in a decline.

Future research may benefit from exploring short–run and long–run mechanisms by which producers react to changes in market fundamentals. The link between weather, input usage, yield, and price merits additional study. In particular, future research may benefit from examining interactions of weather, price, and input use.

[9]Concerns regarding the potential endogeneity of fertilizer prices and biotech adoption are valid. We considered lagged versions of the price and biotech adoption and obtained qualitatively identical results.

Table 1. Variable Definitions and Summary Statistics

Variable	Definition	Mean	Std. Dev.
	........Pooled CRD-Annual Sample (n=405 for full sample)........		
Yield	Harvested acre yield	149.9307	22.0356
May Z-Index	Palmer's Z Drought Index for May	0.9219	2.0796
July Z-Index	Palmer's Z Drought Index for July	0.6899	2.0748
July Temperature	Average temperature for July	74.0758	2.7847
Corn Price	Post-harvest corn futures contracts quoted in February (deflated by cpi)	1.2470	0.2012
Soybean Price	Post-harvest soybean futures contracts quoted in February (deflated by cpi)	2.0499	0.2414
$\ln(P^c/P^s)$	Log of ratio of post-harvest corn and soybean futures price	−0.8029	0.0873
$\ln(P^{APR}/P^{FEB})$	Harvest-time futures contract price change between February and April	0.0101	0.0602
Biotech	Percentage adoption of insect resistant and stacked trait GM corn	31.7394	22.7242
Fertilizer Price	Fertilizer price index (1990-1992=100) (deflated by cpi)	191.9157	68.8275
	........US Aggregate Data 1964-2009........		
Nitrogen Use	Ratio of NASS estimated nitrogen use in corn to total planted acres (,000 tons)	0.0576	0.0088
$\ln(P^c/P^s)$	Log of ratio of post-harvest corn and soybean futures price	−0.8295	0.1066
$\ln(P^{APR}/P^{FEB})$	Harvest-time futures contract price change between February and April	0.0064	0.0574
Biotech	Percentage adoption of insect resistant and stacked trait GM corn	0.0917	0.1693
Fertilizer/Corn Price	Ratio of anhydrous ammonia nitrogen price and corn futures price	0.9795	0.3355

Table 2. Aggregate (Three-State) Fixed Effects Estimates[a]

	Model 1: OLS Fixed Effects		Model 2 OLS Fixed Effects			Model 3 GAM Fixed Effects	
Variable	Estimate	Std. Error	Estimate	Std. Error	Clustered Std. Error	Estimate	Std. Error
Trend / Linear(t)	2.4070	0.6126*	2.6144	0.4141*	0.3002*	1.7049	0.4019*
May Z-Index	−2.1106	0.3309*	−2.1454	0.3217*	0.3865*	−1.9046	0.3122*
July Z-Index	1.8345	0.3122*	1.8290	0.3117*	0.5592*	1.8949	0.3025*
July Temperature	−1.4370	0.3351*	−1.3753	0.3067*	0.2597*	−1.5297	0.2976*
$\ln(P^c/P^s)$			42.1157	9.9959*	9.8308*	29.3856	9.7009*
Corn Price	38.5310	12.6831*					
Soybean Price	−42.2000	10.0082*					
$\ln(P^{APR}/P^{FEB})$	131.5269	18.9683*	133.5784	18.4168*	12.9231*	113.4862	17.8734*
Biotech	0.1494	0.1299	0.1180	0.1104	0.0748	0.2994	0.1071*
Fertilizer Price	−0.0697	0.0279*	−0.0788	0.0197*	0.0139*	−0.0696	0.0191*
Spline(t) Smoothing Parameter						0.9843	
Spline(t) DF						1.22795	
Spline(t) DF Chi-Square						24.0716*	
R^2	0.7493		0.7492			0.7646	
F-test of Elasticities	0.2100						
F-test (p-value)	0.6458						

[a] An asterisk indicates statistical significance at the $\alpha = .10$ or smaller level.

Table 3. State-Specific Generalize Linear Model (GAM) with Spline Time Trend and Fixed Effects Estimates[a]

	Illinois		Indiana		Iowa	
Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Trend / Linear(t)	1.8646	0.8645*	2.6470	0.4943*	−1.1404	1.2349
May Z-Index	−2.8525	0.5595*	−4.1076	0.5454*	−0.8777	0.4615*
July Z-Index	3.4758	0.6315*	3.2965	0.4998*	0.6905	0.4857
July Temperature	−1.1309	0.5514*	−1.1103	0.4989*	−1.1435	0.4634*
$\ln(\mathrm{P}^c/\mathrm{P}^s)$	65.5693	17.0049*	23.0641	14.8147	44.0913	16.9957*
$\ln(\mathrm{P}^{APR}/\mathrm{P}^{FEB})$	165.8448	32.3220*	149.8812	29.1345*	95.6774	30.7760*
Biotech	0.2068	0.2266	0.2252	0.1592	0.9596	0.3114*
Fertilizer Price	−0.0637	0.0356*	−0.1154	0.0372*	−0.0777	0.0278*
Spline(t) Smoothing Parameter	1.0000		1.0000		0.8917	
Spline(t) DF	0.0001		0.0001		2.6783	
Spline(t) DF Chi-Square	0.0001		0.0001		33.2433*	
R^2	0.8215		0.7994		0.7519	

[a]An asterisk indicates statistical significance at the $\alpha = .10$ or smaller level.

Table 4. Yield–Price Elasticity Estimates

Specification	Long-Run Inter-Seasonal	Short-Run Intra-Seasonal
Model 1: OLS With Real Prices	0.2499	0.0085
Model 2: OLS With Price Ratio	0.2732	0.0087
Model 3: GAM With Price Ratio	0.1906	0.0074
Model 4: Illinois (GAM With Price Ratio)	0.4253	0.0108
Model 5: Indiana (GAM With Price Ratio)	0.1512	0.0098
Model 6: Iowa (GAM With Price Ratio)	0.2830	0.0061

[a]Evaluated at 2010 Average Yield of 154 bu/acre and 1996-2010 average intra-seasonal price movement of 0.01.

Table 5. OLS Regression Estimates of Aggregate US Corn Fertilizer Use (1964-2009)[a]

Variable	Estimate	Std. Error	t-Ratio
Intercept	0.0178	0.0042	4.22*
$\ln(P^c/P^s)$	0.0046	0.0053	0.86
$\ln(P^{APR}/P^{FEB})$	0.0155	0.0088	1.76*
Fertilizer Price	−0.0015	0.0019	−0.78
Nitrogen_{t-1}	0.7946	0.0546	14.56*
Biotech	−0.0013	0.0040	−0.31
R^2	0.8725		

[a]An asterisk indicates statistical significance at the $\alpha = .10$ or smaller level.

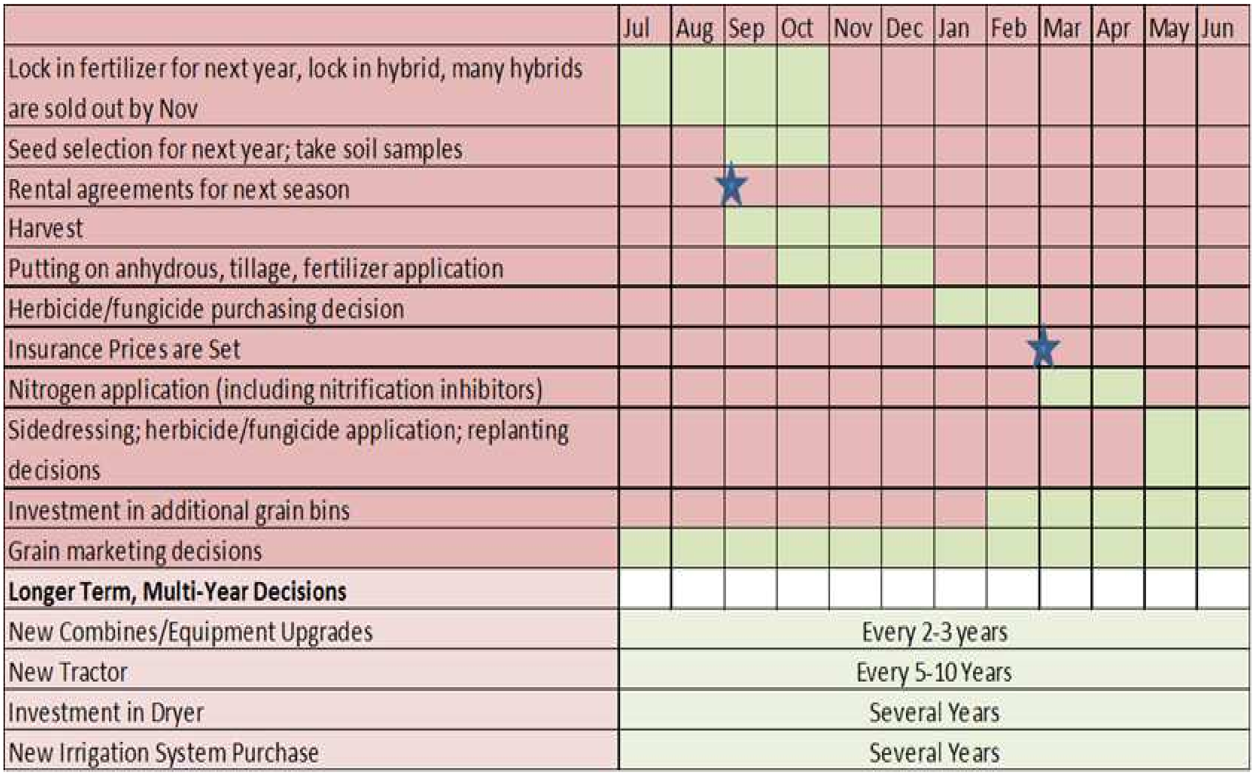


Figure 1: Iowa Corn Growers Focus Group Results of Production Decisions

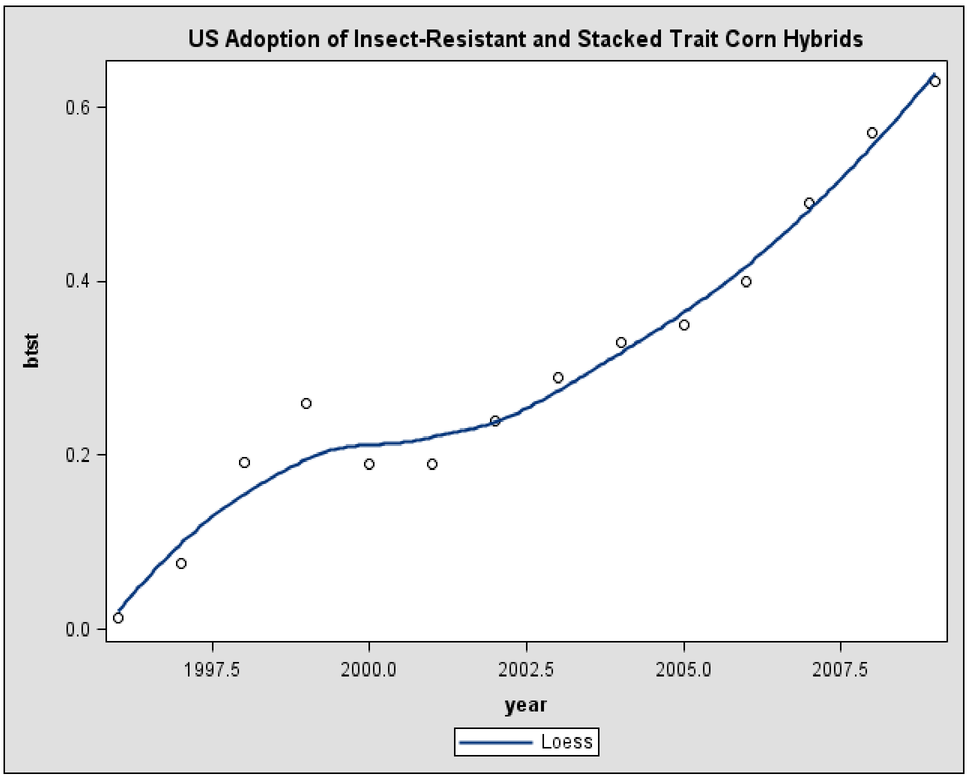
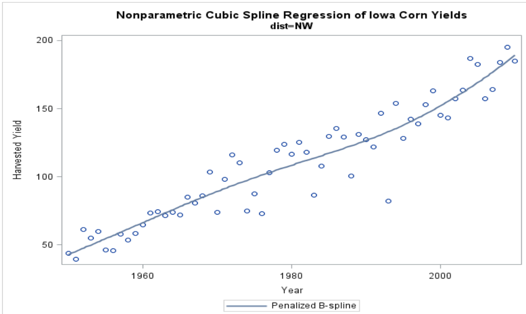
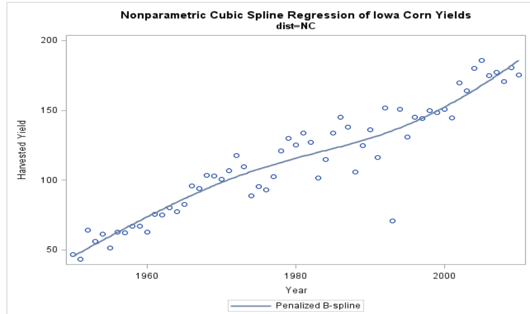


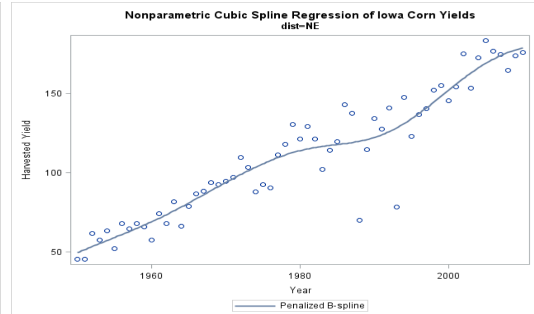
Figure 2: Aggregate Adoption of Insect-Resistant and Stacked-Trait Biotech Corn Hybrids



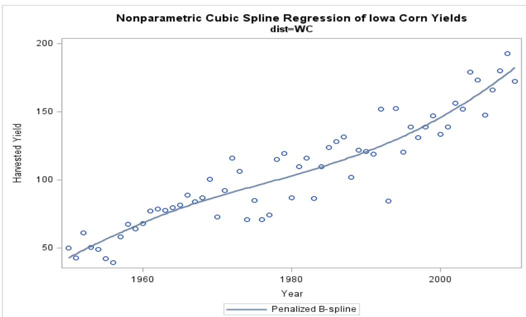
(a) Northwest District



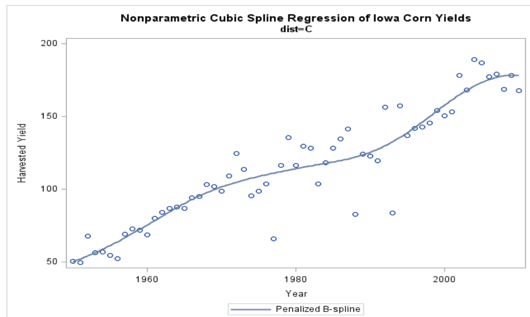
(b) North Central District



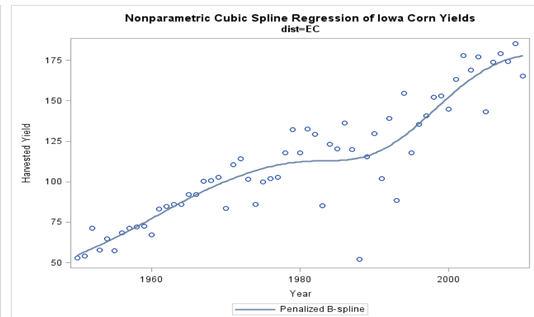
(c) Northeast District



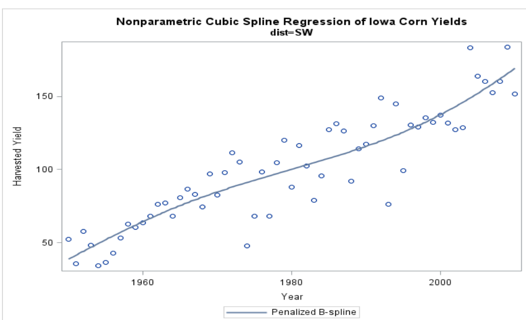
(d) West Central District



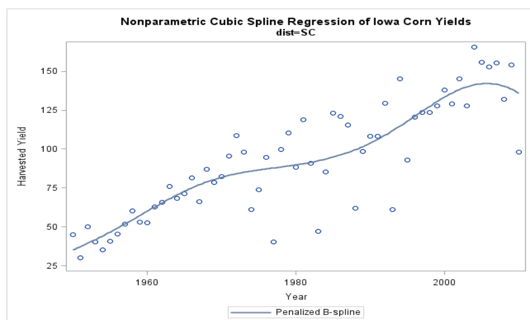
(e) Central District



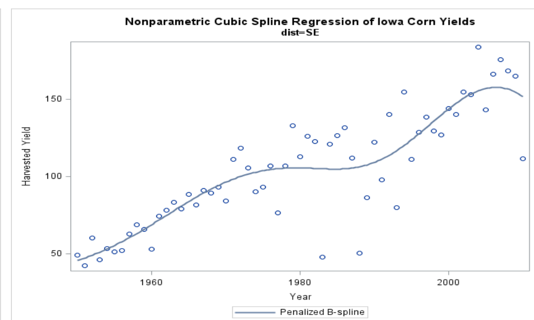
(f) East Central District



(g) Southwest District



(h) South Central District



(i) Southeast District

Figure 3: Non-Parametric Cubic Spline Trends for District-Level Iowa Corn Yields

References

Berry, S.T. 2011, "Biofuels Policy and the Empirical Inputs to GTAP Models," Report to California Air Resources Board, evaluating GTAP.

Choi J. and P.G. Helmberger. 1993. "How Sensitive are Crop Yields to Price Changes and Farm Programs?" *Journal of Agricultural and Applied Economics*, 25: 237-244.

Ervin, D.E., Y. Carriere, W.J. Cox, Fernandez-Cornejo J., R.A. Jussaume, M. Marra, M.D Owen, P.H. Raven, L.L Wolfenbarger, D. Zilberman. 2010. "Impact of Genetically Engineered Crops on Farm Sustainability in the United States." National Academies of Science. Available online at: http://www.nap.edu/openbook.php?record_id=12804&page=R5.

Farrel A.E., R.J. Plevin, B.T. Turner, A.D. Jones, M. O'hare, and D.M Kammen. 2006 "Ethanol Can Contribute to Energy and Environment Goals." *Science* 311: 506-507.

Fargione J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. "Land Clearing and the Biofuel Debt," *Science* 319: 1235-1237.

Griliches, Z. 1957, "Hybrid Corn: An exploration in the economics of technological change," *Econometrica* 25(4): 501-522.

Hastie, T. and Tibshirani, R. (1986), Generalized Additive Models, *Statistical Science*, 3, 297318.

Hayami, Y. and V.M. Ruttan. 1985. *Agricultural Development: An International Perspective* (Johns Hopkins University Press, Baltimore).

Hertel, T., A Golub, A Jones, M. O'Hare, R. Pelvin, and D Kammen. 2010. Effects of U.S. maize ethanol on global land use and greenhouse gas emissions: Estimating market-mediated responses. *BioScience* 60(3): 223-231.

Houck J.P and P.W. Gallagher. 1976. "The Price Responsiveness of U.S. Corn Yields," *American Journal of Agricultural Economics*, 58(4): 731-734.

Huang H. and M. Khanna. 2010. "An Econometric Analysis of U.S. Crop Yield and Cropland Acreage: Implications for the Impact of Climate Change." Paper presented at the Agricultural and Applied Economics Association Annual Meeting, Denver, Colorado, July 25-27, 2010.

Just R.E. and R. D. Pope. 2001. "The Agricultural Producer: Theory and Statistical Measurement." Eds. B. Gardner and G. Rausser. *Handbook of Agricultural Economics.*

Keeney R. and T.W. Hertel. 2009. "The Indirect Land Use Impacts of United States Biofuel Policies: The Importance of Acreage, Yield and Bilateral Trade Responses," *American Journal of Agricultural Economics*, 91(4): 895-909.

Leborde, D. 2011. Assessing the Land Use Change Consequences of European Biofuels Policies. International Food Policy Research Institute, Washington, DC.

Menz K.M. and P. Pardey. 1983. "Technology and U.S. Corn Yields: Plateaus and Price Responsiveness," *American Journal of Agricultural Economics*, 65(3): 558-562.

Nelson C.H. and P.V. Preckel. 1989. "The Conditional Beta Distribution as a Stochastic Production Function," *American Journal of Agricultural Economics*, 71(2): 370-378.

Nerlove, M. 1958. *The Dynamics of Supply: Estimation of Farm Supply response to Price.* Baltimore: Johns Hopkins University Press.

Roberts M.J. and W. Schlenker. 2010. "Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate." National Bureau of Economic Research. Working Paper 15921.

Schlenker, W. and M. J. Roberts. 2006. "Non-linear Effects of Weather on Corn Yields." *Review of Agricultural Economics* 28(3): 391-398.

Schlenker, W. and M. J. Roberts. 2009. "Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change." *Proceedings of the National Academy of Sciences* 106(37): 15594-15598.

Sunding D. and D. Zilverman. 2001, "The Agricultural Innovation Process: Research and Technology Adoption in a Changing Agricultural Sector." *Handbook of Agricultural Economics*, 1(1): 207-261.

Searchinger T., R. Heimlich, R.A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, T. Yu., 2008, "Use of U.S. Croplands for Biofuels Increase Greenhouse Gases Through Emissions from Land-Use Change," *Science* 319: 1238-1240.

U.S. Government Printing Office. 2007. PL110-140. Available online at: www.usgpo.gov/fdsys/pkg/PLAW-110publ140/pdf/PLAW-110publ140.pdf

Wahba, G. (1990), *Spline Models for Observational Data*, Philadelphia: Society for Industrial and Applied Mathematics.