Impact of Drought Stress on Transgenic Corn Seed Technologies in the United States: A Comparative Analysis

by

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Abstract

Corn grain yield per acre has increased over 450% in the United States over the last 80 years. Continued increases in productivity may be aided by the advancement and adoption of improved transgenic corn seed varieties, but may be hindered by increased frequency and severity of agricultural drought. To test the hypothesis that current transgenic corn seed varieties are more drought tolerant than conventional seed varieties, stochastic frontier analysis is applied to per-acre yield functions for four alternative seed technologies using field-level, cross-section data from 2005 and 2010 surveys. Palmer's Moisture Anomaly "Z-index" for short term drought is incorporated in linear and quadratic terms for the growing season months of June, July, and August. Nine frontier regressions are estimated for each year: one for the national corn industry, one for each of four resource regions with interactions of seed variety and drought variables, and one for each of four alternative corn seed technologies with interactions of resource region and drought variables. Estimates are reported for factor elasticities, drought impacts and technical efficiencies. Results indicate that average technical efficiency is higher for certain transgenic seed varieties, yet these varieties also tend to have a larger significant negative marginal yield response to increased drought levels. Results may be sensitive to growing region, drought timing and severity, and level of technology adoption. This analysis may benefit corn producers choosing between alternative corn seed varieties and seed developers planning characteristics for future transgenic corn seed technologies.

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List of Abbreviations

APHIS	Animal and Plant Health Inspection Service
ARMS	Agricultural Resource and Management Survey
BLUE	Best Linear Unbiased Estimator
Bt	*Baccillus thuringiensis*
BtECB	*Baccillus thuringiensis* European Cornborer
BtCRW	*Baccillus thuringiensis* Corn Rootworm
C-D	Cobb-Douglas
CDO	Climate Data Online
CRD	Crop Reporting District
CRW	Corn Rootworm
ECB	European Cornborer
ERS	Economic Research Service
FRR	Farm Resource Region
GE	Genetically Engineered
HRV	Herbicide Resistant Varieties
IRV	Insecticide Resistant Varieties
MLE	Maximum Likelihood Estimator
OLS	Ordinary Least Squares
NASS	National Agricultural Statistics Service

NCDC	National Climate Data Center
NESDIS	National Environmental Satellite, Data, and Information Service
NOAA	National Oceanic and Atmospheric Administration
NON	Non-transgenic Varieties
NRC	National Resource Council
PDSI	Palmer's Drought Severity Index
PIK	Payment in Kind
STK	Stacked HRV and IRV Varieties
TE	Technical Efficiency
USDA	United States Department of Agriculture
USDOC	United States Department of Commerce

I. Introduction

Agricultural Productivity

Aggregate agricultural total factor productivity in the United States increased 270% from 1948 to 2004. This overall increase in efficiency of aggregate input use is explained by increased use of capital intensive inputs, like chemical fertilizers and agricultural machinery, as well as employment of the latest agricultural technologies and agronomic practices, such as hybrid seed varieties and precision farming techniques, that altogether increase yield per unit of land and reduce total labor requirements (Fuglie, McDonald and Ball 2007). This recent trend in productivity is especially true for U.S. corn (*Zea mays* L.). Figure 1 graphs total production, total acres harvested, average per-acre yields and average per-bushel price for corn grain in the United States from 1900 to 2010. Total corn for grain production increased 330% from 2.87 million bushels in 1955 to 12.45 million bushels in 2010, with a growth rate trend of about 2.8% per year (figure 1a). This is compared to a mere 0.8% increase in production between 1935 and 1955 and an actual 0.9% reduction from 2.66 million bushels in 1900 to just over 2 million bushels in 1935. Total acres harvested for corn grain increased a modest 19% from 68,482 acres in 1955 to 81,446 acres in 2010, which may be greater than the 1964 low of 55,369 acres but is well below the high of 102,267 acres in 1910 (figure 1b). Thus, the primary reason for the greater than threefold increase in total corn grain production over the last half century is an increased productivity per acre.

The average per-acre yield for corn grain between 1900 and 1935 was 26 bushels, with a slightly negative trend of 0.4% per year (figure 1b). From 1935 to 1955, average per-acre production jumped to over 40 bushels, an estimated 58% increase in per unit productivity. This rise in productivity continued at a growth rate trend of about 2.1% per year into the first decade of the 21st century to reach an average of over 150 bushels per acre from 2004 to 2010. This is a per unit increase of over 250% from 1955 and over 450% from the pre-1936 average. The argument that the increased total efficiency of agricultural production, and the resulting shift in the agricultural supply curve, has helped keep agricultural commodity prices low relative to non-farm products may also hold true for corn production specifically (Fuglie, McDonald and Ball 2007). The nominal national average price received per bushel of grain corn was $0.67 from 1900 to 1935 (figure 1c). This increased to over one dollar by 1943 and remained around $1.25 per bushel until 1973, when the nominal price jumped above $2 for the first time to $2.55. Prices became more volatile after 1973 yet movement managed to remain centered on an average of about $2.35 per bushel through 2006.

The last 4 years of the decade saw a dramatic swing in the nominal price of corn to $5.40 per bushel in 2010. Converting this last period's prices into real dollars using the USDA farm prices received index for food grain crops[1], it is apparent that the real value of grain corn peaked in 2008. This sharp rise in the price of corn corresponds with the global increase in food prices leading to the food price crisis of 2008 (Mittal 2009). The slow increase in the price for food grain relative to the rapid increase in cost of non-farm products over this period is seen clearly by plotting the farm prices received index for food grain alongside the farm prices paid index for all input commodities, interests, taxes and wages (figure 1d). The two indices remained close from 1910 to about 1955, then the prices paid index begins to increase at a rate and shape resembling the growth in total

[1] 1990-1911 base.

corn production while the prices received index lags below. Thus, apart from the exogenous macroeconomic factors contributing to a few major upward shifts, per bushel corn prices have remained relatively low during a period of impressive growth in productivity, benefiting consumers with lower prices for corn based products and providing greater food security through increased total supply.

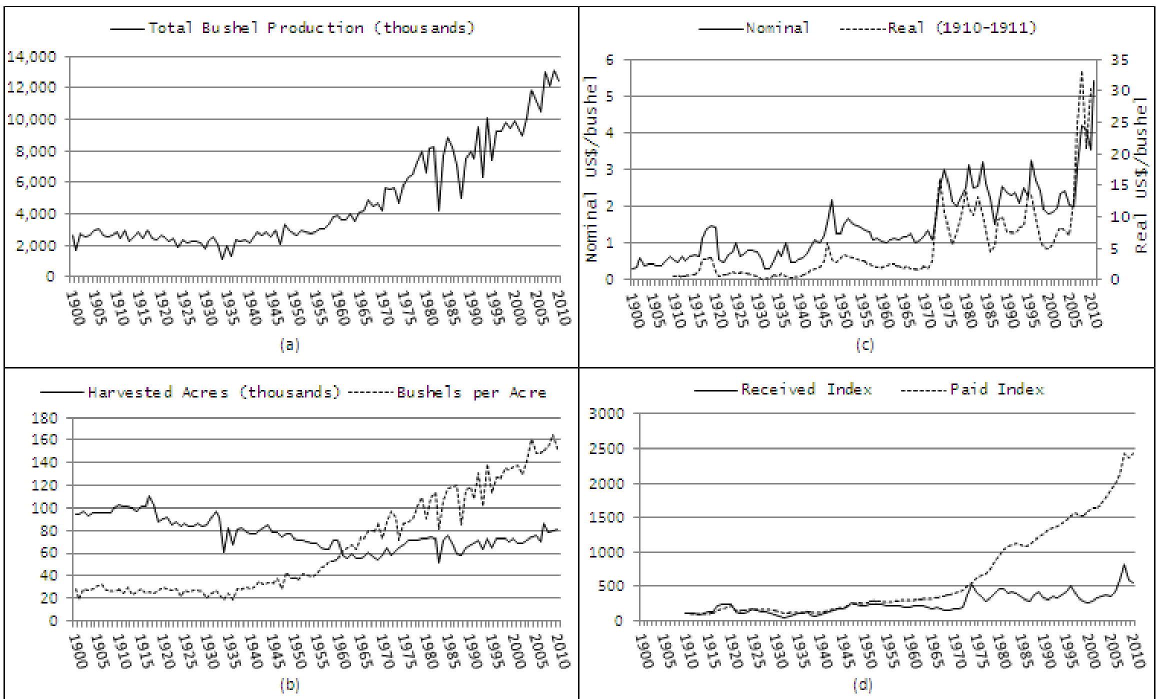

Figure 1. Historical trends for United States corn production from 1900 to 2010[2].

Research Objective

Two major questions arise when considering the future of agricultural production: (1) can further improvements in per-acre productivity be gained through the development of newer, better technologies and adoption of additional improved practices, and (2) what major exogenous factors could be introduced into the market or production system that

[2] Source: USDA 2011 Crop Production Historical Track Records.
Available at : http://www.usda.gov/nass/PUBS/TODAYRPT/croptr11.pdf

could negatively impact production and/or cause further price increases? One practice that holds promise for continued increases in per-acre productivity is the adoption of first generation transgenic hybrid corn seed varieties genetically engineered to aid growers in mitigating yield reducing damage from weed and insect pests. One potential negative shock to this productivity would be an increase in the frequency and severity of drought conditions in major corn growing regions as a result of changing global climate conditions [3](Fedoroff *et al.* 2010). This study estimates the relative tolerance of widely adopted transgenic corn seed technologies to drought stress, focusing on comparing the estimated marginal impacts of drought conditions for four categories of alternative seed varieties while accounting for technical inefficiencies in production.

Specifically, to test the hypothesis that current transgenic corn seed varieties are more drought tolerant than conventional, non-genetically engineered corn seed varieties, stochastic frontier analysis is applied to per-acre yield functions for four alternative seed technologies using field-level, cross-section data from 2005 and 2010 USDA Agricultural Resource Management Survey (ARMS) corn production practices data, incorporating Palmer's Moisture Anomaly "Z-index" for short term drought severity over three months of the summer corn growing season. Nine frontier regressions are estimated for each year: one for the national corn industry, one for each of four alternative corn seed technologies with interactions of resource region and drought variables, and one for each of four resource regions with interactions of seed variety and drought variables. Results from this analysis may aid corn producers when making future seed variety decisions and seed providers in planning characteristics for future transgenic seed technologies.

[3] Increasing per-acre yield in current drought prone regions is equally important apart from climate change.

II. Background

Agricultural Biotechnology Adoption

In the last 16 years, the transgenic agricultural biotechnology industry has generated multiple genetically engineered (GE) seed traits, benefiting commercial field crop producers by providing additional options in production management and ultimately leading to over 91% of all Unites States' corn, cotton, and soybean acres being planted in GE seed varieties by 2010 (Fernandez-Cornejo 2011). GE seed was first introduced to the U.S. commercial field crop industry in 1996 in the form of two transgenic seed varieties engineered to benefit producers through improved pest control. Developed for corn, soybean and cotton, herbicide-resistant varieties (HRV) conferred to crop plants a special form of the enzyme known as EPSPS (5-enolpyruvylshikimate-3-phosphate synthase)—an enzyme common to all photosynthetic plants—that is resistant to specific broad spectrum herbicides effective against most field crop weed pests (Padgette, et al. 1995). Developed first for corn and cotton, insect-resistant varieties (IRV) transferred genetic material from the naturally occurring soil bacterium *Bacillus thuringiensis* (Bt) into crop plants, enabling plant specific resistance to damage from certain economically important field crop insect pests (NRC 2010).

Initial adoption rates for GE corn—measured as percent of total crop acreage—were low compared to that of other GE crops: HRV corn acreage was 5% and IRV corn acreage was 8% in 1997. HRV corn acreage remained near 8% over the next four years while IRV corn acreage leveled off around 21% by 2001 (Fernandez-Cornejo and McBride 2002). In 2002, "stacked" GE seed with IRV and HRV traits utilized in the same seed became available, and in 2003 an IRV trait was introduced that provided resistance to an additional insect pest—southern corn rootworm (CRW)—responsible for much greater corn crop yield loss (NRC 2010). IRV then included a Bt trait for corn borer pests (BtECB) and/or a Bt trait for corn rootworm pests (BtCRW). With these advances, seven different GE seed varieties were available to U.S. corn producers by 2005, specifically: HRV only, BtECB only, BtCRW only, stacked HRV plus BtECB, stacked HRV plus BtCRW, stacked BtECB plus BtCRW, and stacked HRV plus BtECB plus BtCRW (USDA, ERS 2005). By 2010, this list expanded to include an option to stack multiple herbicide resistant traits, the addition of Bt traits to protect against corn earworm pests, and any combination of these traits with those previously listed (USDA, ERS 2010).

To facilitate comparison, these alternatives are grouped and referenced in the following manner consistent with USDA recording conventions. Any variety with herbicide resistance only will be termed HRV for "herbicide resistant varieties", any variety with insect resistance only—of any combination—will be termed IRV for "insect resistant varieties" and any variety with a combination of any variety termed HRV with any variety termed IRV will be termed STK for "stacked varieties". These GE seed technologies are alternatives to conventionally developed seed varieties[4], termed NON for "non-GE varieties." With multiple seed technologies available, producers are able to select the appropriate traits for their specific agronomic needs. From 2005 to 2010, adoption rates changed from 17% of corn acreage in HRV, 24% in IRV, and 9% in STK varieties—a combined 52% of total U.S. corn acreage in GE seed—to 23% in HRV, 16% in IRV, and 47% in STK varieties, totaling 86% of U.S. corn acreage (Fernandez-Cornejo

[4]This includes seed traits developed using advanced techniques that are by definition not transgenic.

2011).

On December 21, 2011, the Monsanto and BASF Companies announced that the USDA had deregulated the first drought-tolerant GE corn seed for commercial release, a product of the companies' joint research efforts (Monsanto 2011; BASF 2011). Designated as event MON87460, the new trait was determined by the USDA Animal and Plant Health Inspection Service (APHIS) as having "no significant impact," finding that "Monsanto's corn event MON87460 is unlikely to pose a plant pest risk and therefore is no longer subject to [USDA] regulations governing the introduction of certain GE organisms"(USDA, APHIS 2011a). Combining the new drought tolerant trait with multiple HRV and IRV traits stacked in their current line of Genuity® products and marketed by the trade name DroughtGard™, Monsanto is planning on-farm field trails during the 2012 season in the Western Great Plains region, where fields are mostly rain fed, frequently suffer from "limited-water stress conditions" and have yields more than 15% below the national average. Full commercial release is expected for the 2013 season (Monsanto 2011, 2012).

Agricultural Biotechnology Effects on Yield

From surveys of early GE corn seed adopters conducted in 1996, 1997 and 1998, Pilcher et al. (2002) find the primary reason farmers adopted IRV was to reduce yield loss due to pest damage, and that a large majority of farmers perceived good or outstanding control of ECB. While perceived effectiveness of control and reported increases in yield in comparison to NON varieties were high for all years—26-38% reporting similar yields and 45-60% reporting higher yields across all states surveyed—

they were highest in 1997 when pest pressure was most significant. In 1998, the mean increase in reported yields was 10.3 ±0.2 bushels per acre. Of the 7% perceiving reduced yields with IRV in 1998, the mean of yield reductions reported was 14.7 ±1.1 bushels-per-acre. In 1997, the mean increase in reported yields compared to non-adopters was 16.2 ±0.2 bu/acre. Yet, while yields were 14.3 ±0.7 bu/acre less on average over all states for the 7.6% that perceived reduced yields with IRV in 1997, average reported reductions remained higher than reported increases in 3 of the 6 states surveyed.

These responses appear consistent with experimental results comparing IRV with BtECB traits to high-yielding near isolines[5] in central and eastern corn growing states. Experimental comparisons in Missouri showed that insect damage was significantly less and yields significantly higher for IRV than for NON when no other treatment was employed (Barry et al. 2000). While damage was always significantly less with IRV, harvestable yields were frequently not significantly different and at times significantly less than NON under comparable insecticide treatment practices, depending on exact seed variety and infestation levels. Subsequent field experiments in other states corroborate this result of inconsistent yield differences dependent upon hybrid variety, additional treatment practices and insect infestation (Dillehay et al. 2004, references therein). For example, increased insect damage control resulted in higher yields on average over all tested IRV in 4 out of 6 test plots in Pennsylvania and Maryland in 2000, but for only 1 of 4 plots in 2001 and 2002 when natural pest presence was lower (Dillehay et al. 2004).

In its final environmental assessment in November 2011, APHIS relates Monsanto's determination that corn plants with the MON87460 event are "expected to

[5] Conventionally bred varieties with similar hybrid characteristics.

reduce yield loss by six percent or more under water-limited conditions compared to conventional corn." APHIS continues by stating that regionally marketed conventional varieties bred using advanced non-transgenic techniques "apparently have similar drought tolerant properties as MON87460," citing Pioneer Hybrid's Optimum Aquamax® with a demonstrated 5% reduction in yield loss (USDA, APHIS 2011b). APHIS further determines that the MON87460 event will likely not enable an expansion of cultivation into "novel and non-arable areas" significantly different from that allowed by current non-transgenic varieties, reiterating the conclusion that "MON87460 is not significantly different from currently-available corn varieties under both water-sufficient and water-limited conditions" in regard to "corn growth, development, and abiotic stress," and that "the magnitude of drought tolerance in MON87460 is observed in other regionally adapted, drought tolerant corn varieties" (USDA, APHIS 2011b).

Drought Effect on Yield

Drought, in general, can be defined as “a meteorological anomaly characterized by a prolonged and abnormal moisture deficiency” relative to established historical conditions (Palmer 1965). This definition allows for drought to occur in historically arid or historically humid regions of the world. More specific concepts of drought arise from the perceived importance of different impacts experienced because of meteorological drought. For instance, agricultural drought is linked primarily to the availability of water to crop plants during the growing season in the form of soil moisture. Perceptions of drought conditions vary additionally by the scope, severity and duration of the relative moisture deficiency, leading to numerous independent drought measures (Heim 2002, Keyantash and Dracup 2002, Quiring 2009). The most commonly referenced general measure is Palmer's Drought Severity Index (PDSI), which indexes accumulated moisture levels above and below an historical, geographically standardized mean (Palmer 1965, Alley 1985).

The significant negative physiological response of crop plants to soil water deficiency is well understood. Corn plants depend on water for growth at all stages, with the strongest yield influence during periods of reproductive development (Nesmith and Ritchie 1992a, 1992b; Earl and Davis 2003; Fageria, Baligar and Clark 2006). As a limiting factor of production, extreme water deficit can lead to complete crop failure. In the productive corn growing regions of temperate North America, extreme long term drought events occur infrequently but can have devastating effects on total production. Figure 3 plots the average monthly PDSI for the top five corn producing states[6] in the United States' "Corn Belt" alongside the percentage deviation of total annual U.S. corn grain production from the five-year moving average growth trend[7]. PDSI values near zero denote normal conditions. Positive values mark periods of excess moisture while negative values correspond to moisture deficiency, both increasing in severity as the index increases in absolute value.

Dramatic reductions in the production trend correspond with well known periods of extreme drought in the mid 1930's across most Mid-Western states, and again in 1988 in the heart of the Corn Belt. Aggregate production is not perfectly correlated with drought over time because of the other technological and macroeconomic factors

[6] In order of acreage and total production: Iowa, Illinois, Nebraska, Minnesota, Indiana.
[7] Annual production values are aligned with monthly PDSI values in July.

contributing to total production levels. For instance, the sharp negative deviation from the aggregate growth trend in 1983 is a direct response to the Federal Payment-in-Kind (PIK) program that encouraged farmers to reduce production in order to lower government-held surpluses (Fuglie, McDonald, and Ball 2007). The close relationship between available moisture and production prior to the 1930's reflects the greater dependence of early, low input production practices on immediate weather conditions.

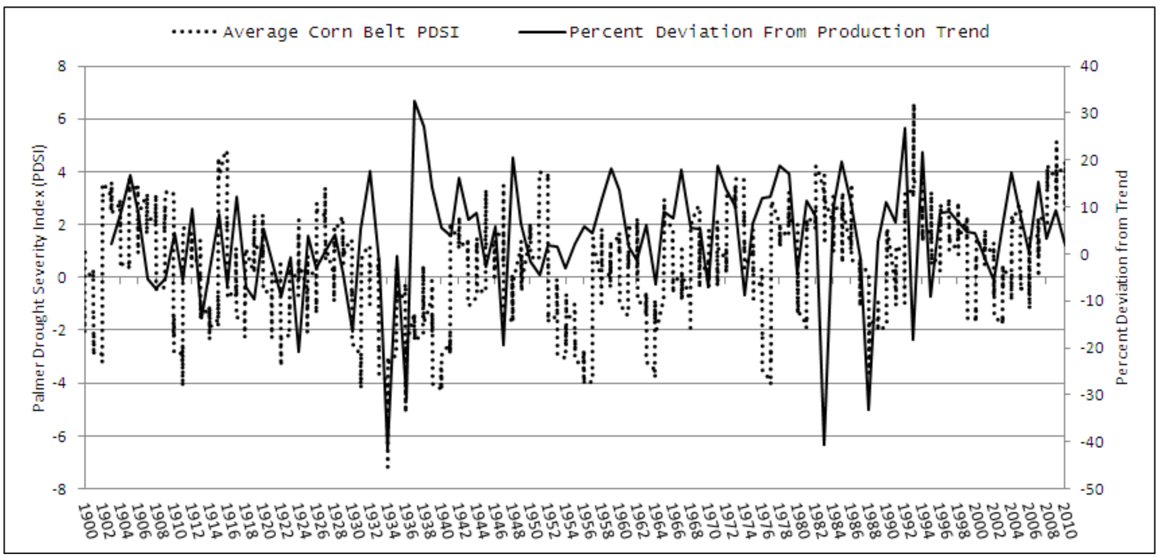

Figure 2. Average PDSI of top five Corn Belt states and percent deviation of total U.S. annual corn production from five year moving average trend.

The large positive deviation from the production trend that is apparent in 1938 is a result of total production turning a positive corner after a drought induced drop, compounded by initial adoption of improved, hybrid seed technology (Sutch, 2011). Actual production did not change much in total terms, but the percentage change was significant as drought lessened and yield levels recovered. The strength of the year to year relationship between drought and production decreased as per-acre productivity accelerated due to increased use of capital intensive practices since the 1940s. The extended, but less acute, drought during the 1950's corresponds to a period of slower growth in production. The production trend in this period is positive because of increased per-acre productivity, despite prolonged soil water deficits. Another point of particular interest is in the opposing peaks between the average PDSI and deviation from production trend that occurred during the great Midwest flood of 1993. This event demonstrates the fact that drought indices like the PDSI measure not only moisture deficit but also moisture excess: severe deviations in either direction from the norm will have a strong negative impact on crop yield.

Sutch (2011) suggests that the upswing in the corn production trend in 1938 is a consequence of farmers reacting positively to the devastating 1934 and 1936 droughts by adopting superior, “double-cross” hybrid seeds over previously preferred “open-pollinated” varieties faster than they would have otherwise. Hybrid corn seed was available in 1925, but adoption was only at a tenth of one percent in 1933. From 1936 to 1939, hybrid seed adoption reached at least 10% of all corn acreage in Iowa, Illinois, Indiana, Wisconsin, Minnesota, Ohio, Nebraska, and Missouri, and complete, nationwide adoption was achieved by 1960. Thus, the transition to hybrid seed technology marked the beginning of the steady per-acre productivity gains seen over the last seven decades, relying heavily on the complex interactions between new varieties' improved characteristics and the availability of complementary inputs and machinery (Griliches 1957; Johnson 1960; Castleberry, Crum, and Krull 1984; Sutch 2011).

Although it is clear that total per-acre corn productivity has increased, and that this can be explained primarily by the wide adoption of continually improved seed varieties and capital intensive production practices, it is less clear whether the most recent seed technologies have made corn production more or less tolerant to drought. As noted above, there was a significant negative deviation from the production growth trend in response to the extreme drought of 1988, but no notable aggregate production response to short drought periods in the sixties or seventies. The aggregate growth trend even remained positive over the prolonged drought of the 1950's. Thus, seed varieties available prior to the use of transgenic technologies seemed to be improving yields under moderate drought stress conditions, yet were still susceptible to severe drought stress. Seed technologies of the last 20 years have yet to be tested by severe drought. Recent yields may have benefitted from adoption of advanced seed technologies, but it is hard to separate the technology impact from that of the relatively mild weather conditions.

Impact of Biotechnology on Drought Tolerance

Yu and Babcock (2010) conclude that “corn is becoming less susceptible to drought” after estimating fixed-effects regressions of county-level corn yield on a self-constructed county-level drought index, using a panel of 98 selected counties across 11 crop reporting districts (CRD) in Indiana and Illinois from 1980 to 2008. Interpretation of the statistically significant point estimates from the log-log model for corn indicates that drought has a negative impact on corn yields, this impact has lessened in percentage terms over time, the marginal effects of severe drought is less than moderate drought, and that "over time, losses in corn bushels under severe droughts are not reduced as much as under minor droughts" The authors propose that this result supports the hypothesis that recently adopted transgenic corn seed varieties—developed to reduce pest pressure damage—have indirectly contributed to increased drought tolerance by providing an environment for stronger, healthier plants able to withstand higher levels water deficit stress (Yu and Babcock 2010).

Roberts and Schlenker (2011) take a slightly different approach in estimating the correlation of extreme weather and corn yields. With a stated purpose to "examine how heat tolerance and drought tolerance has changed over time," a restricted cubic spline, fixed effects regression model is estimated with total corn yields from all counties in Indiana from 1901 to 2005 using county-level annual precipitation and separate county-level measures of moderate heat and extreme heat carefully constructed from daily temperature micro-data. These specific weather variables are included after confirming that corn yields have a non-linear relationship with cumulative high temperature—yield increasing with temperatures up to a maximum threshold then decreasing at a greater rate with temperatures beyond this threshold—and finding that spatially-specific cumulative exposure to extreme heat is the "strongest single predictor of yield outcomes" (Davenport 1907; Ritchie and Smith 1991; Schlenker and Roberts 2006; Schlenker and Roberts 2009). Results are displayed by generating multiple, time-period specific graphs of predicted yield responses to changes in a single weather variable holding all other variables fixed at their mean values (Roberts and Schlenker 2011).

The negative impact of deviations of precipitation from its optimum decreased to near insignificance in 1990. This is proposed to relate to increased irrigation on farms "more prone to dryness" as well as "increased drought tolerance" bred into seed varieties. Yield later takes on a negative linear relationship to increased precipitation that is left un-explained. Both moderate heat and high heat reached interesting turning points in 1960. It is then that the previously positive linear relationship between yield and moderate heat reached a point of zero slope, and the previously strong negative linear relationship between yield and high heat reached its shallowest slope. This marks the point of lowest dependence of yield on moderate temperature accumulation and the highest tolerance of yield to high temperature accumulation. From 1960 to 2005, the predicted moderate heat to yield relationship returned to the expected positive slope and the predicted negative high heat to yield relationship returned to levels equal to those predicted for 1901 to 1923. The result that corn production is less tolerant to extreme heat in 2005 than in the years prior to the adoption of improved hybrids is unexpected given the nearly four-fold increase in average per-acre yields achieved over this same period (Roberts and Schlenker 2011).

While Roberts and Schlenker reference the possible increased drought tolerance of hybrid seeds in general[8], and Yu and Babcock base their hypothesis of increased drought tolerance on the indirect benefits of transgenic biotechnology specifically, neither study examines the interaction of drought and biotechnology explicitly. Vado and Goodwin (2010) separate the relatively fair weather effect in recent years from the level of transgenic biotechnology adoption as possible explanations for increased yields over time. Using county-level average yield per acre as the dependent variable and county-level accumulated moderate heat, accumulated high heat, total precipitation, and percent of acreage in transgenic seed as explanatory variables, they estimate a log-linear, fixed effects panel of 199 selected counties[9] from the Corn Belt states of Iowa, Illinois,

[8] In the form of yield response to precipitation only, assuming drought is separable from heat.
[9] Based on data availability.

Missouri, Indiana, and Ohio for the years 1981 to 2008. The influence of biotechnology adoption on yield sensitivity to weather is captured by interacting adoption level variables with high heat accumulation and precipitation. Results indicate that a one percent increase in GE corn adoption levels—particularly IRV corn—explain as much as 44% of yield increase, and that the negative effect of high heat diminishes with increased adoption. Biotech interactions with precipitation are insignificant.

Collectively, these studies suggest that the improved pest resistance inherent in widely adopted IRV and STK corn seeds have increased the yield potential in both optimum and adverse growing conditions. The increased sensitivity of total corn yields to high heat presented by Roberts and Schlenker (2011) and the increased tolerance to high heat with increased GE seed adoption presented by Vado and Goodwin (2010) do not necessarily disagree: the negative annual extreme heat impact reached a maximum by about 1990 and, although still significantly larger than in 1960, showed a slight decrease by 2005 (Roberts and Schlenker 2011). GE seed adoption began in 1996, during the time of the estimated decrease in the high heat impact on yield. Thus, the period of increased tolerance due to GE adoption corresponds with this period of reduced heat impact. The logical next step in analyzing the relative tolerance of transgenic corn seed yields to drought is to isolate the influence of adverse weather on alternative corn seed technologies facing similar conditions. It is the purpose of this study to compare the influence of drought on per-acre yields for three transgenic corn seed varieties to the impact of drought on conventionally developed seed varieties using field-level production variables in micro-econometric models grounded in economic production theory.

III. Methods

Agricultural Production Functions

The econometric estimation of the effect of weather on crop yield has a long and extensive history, beginning with Henry Wallace's time-series regressions of state average corn yields on monthly temperature and rainfall variables (Wallace 1920). Even Sir R.A. Fisher, recognized for laying the statistical foundation for modern regression analysis by effectively synthesizing and expanding upon the strengths of previous statistical theories, nurtured his ideas through applications in agricultural meteorology (Anderson 1996). Fisher presented some of his most significant scientific contributions through a series of studies on yield variation conducted during his time as Chief Statistician at the Rothamsted Agricultural Experiment Station in Hertfordshire, England (Box 1976; Aldrich 2005). In one of these studies, "The influence of rainfall on yield of wheat at Rothamsted," Fisher obtains estimates of the "partial correlation coefficients" for rainfall over the growing season, noting the significantly positive or negative values for different periods and relating these impacts to plant growth stages and alternative treatments over experimental test plots (Fisher 1925).

These early regressions, and those of the more recent literature reviewed above, fall into a broad class of estimations termed yield response or crop growth models, of which innumerable examples exist. Yield response models typically regress some measure of crop output on agronomic and/or climatic input variables to estimate a biophysical input-output relationship. The coefficient estimates from these models can afterwards be applied to yield simulation models to predict yield outcomes under different growing conditions. Yield response models have become increasingly popular in recent decades because of a strong interest in predicting potential changes in agricultural yield under various climate change scenarios. Recent advances in yield response models, such as Schlenker and Roberts (2006), are mostly in the improved measurement of selected weather variables, leading to more precise weather impact estimates, thus more accurate yield simulations.

Econometric agricultural production functions differ from yield response models in that they aim to estimate the technical relationships between economic factors of production and agricultural output within the framework of economic production theory (Heady and Dillon 1961). While the classical theory of production and the concept of an economic production function, or transformation function, is deeply rooted in the history of economic thought, the first attempts to econometrically estimate the technical relationships within a production function were made by Cobb and Douglas (1928), using aggregated U.S. manufacturing data. Agricultural economists later adopted the unrestricted[10] Cobb-Douglas function in econometric analysis of farm-level, agricultural production relationships (Kamiya 1941; Tintner 1944; Tintner and Brownlee 1944; Heady 1946).

Unlike yield response models, econometric agricultural production functions are not restricted to biophysical inputs and output only. For instance, Tintner (1944) mixes the dependent variable of economic profits with explanatory variables that include number of acres in production, months of labor and various cash expenses. No matter what the physical or economic units, these variables usually fall into the classical production factor categories of capital, labor and land. Heady (1952) reminds us of an

[10] Durand (1937) first relaxed the constant returns to scale restriction of the original Cobb-Douglas function.

additional input factor not to be excluded from the production relationship: management ability. According to Warren (1913), "more farmers fail because of poor farm management than because of poor production." Fetter (1915) expounds with this appropriate summary,

> "The ability to choose and to do wisely is an element in personal skill in every economic activity. This quality in the man is managing ability, and the action of directing economic activity is business management...Almost every business today requires from time to time additions of capital, temporary or permanent...The factors bought - equipment, materials, and labor - are to be skillfully and economically combined to secure a product worth more than it costs...For the performance of this task of combining the factors a management must have, somewhere in the personnel, adequate technical knowledge of methods, processes, and materials, and experience in the art of applying the knowledge."

Considering yield response models and production functions together, a fully specified, simple model of agricultural production would include variable factors of production of an economic nature (X) as well as an agronomic/climatological nature (Z), all of which are employed in the transformation of available resources into an agricultural product, $Y = f(X, Z)$. Included within X would be vectors of variables representing physical capital (C), labor (L), land (D), and executive ability, or management (M). Since most physical agronomic inputs, such as fertilizers and pesticides, could be classified as variable capital factors and the productive capacity of the soil could be classified under land, remaining within Z would be exogenous weather variables (W) such as precipitation and temperature. A complete yield function would then be expressed as $Y = f(C, L, D, M, W)$.

While all factors identified influence the level of final output, not all factors are within the producer's control to the same degree. In the long-run, a producer's obvious first choice is of what to produce given the location, or, inversely, where to produce given the crop. Choice of location can be between entire regions of a nation or between fields of a farm. The regional decision puts long run weather expectations and general land quality and quantity under the producer's control, while within farm decisions make field-specific land quality and quantity a short run choice variable. Regional production practices can be expected to be adapted to local weather patterns with an arguably known probability of weather variation, but exact levels of weather inputs introduced over a year's growing season is beyond the producer's control (McQuigg and Doll 1961). The unpredictable flood or drought occurrence moves actual values of weather variables into the realm of uncertainty. The challenge to integrating all relevant factors into a single econometric production function is in proper specification of the input-output relationship using established economic theory as well as measurement, identification and collection of chosen variables (Heady and Dillon 1961).

Using the unrestricted Cobb-Douglas (C-D) production function as a starting point, a common stochastic agricultural production relationship for agricultural firm $i = 1, \dots, N$ is specified as $Y_i = AC_i^{\beta_{i1}} L_i^{\beta_{i2}} D_i^{\beta_{i3}} e^{\varepsilon_i}$; where Y_i is total farm output as the quantity of a single product or the value of a single product or group of products; C_i is the value of productive capital, L_i is quantity of labor and D_i is quantity of land used in the production of Y_i; ε_i is the idiosyncratic error term capturing stochastic noise; the beta exponents are coefficients to be estimated; and the first term, $A = e^{\alpha_0}$, is a constant to be estimated representing the total factor productivity of the industry. This functional form is a convenient representation of technology in that it is easily estimated using least squares regression when transformed into logarithmic form, $\ln Y_i = \alpha_0 + \beta_{i1} \ln C_i + \beta_{i2} \ln L_i + \beta_{i3} \ln D_i + \varepsilon_i$, giving the coefficient estimates direct interpretation as the economically meaningful elasticities of production with respect to each input. This is seen from the exponential form using capital as an example, where the marginal product of capital is $MP_C = \partial Y/\partial C = A\beta_1 C^{\beta_1 - 1} L^{\beta_2} D^{\beta_3}$ and the elasticity of production with respect to capital is $\mathrm{E}_{\mathrm{YC}} = (\partial Y/\partial C) \cdot C/Y = A\beta_1 C^{\beta_1 - 1} L^{\beta_2} D^{\beta_3} \cdot C/AC^{\beta_1} L^{\beta_2} D^{\beta_3} = \beta_1$.

The C-D form is also favored because it allows for diminishing marginal returns to each factor, holding other inputs fixed, while preserving valuable degrees of freedom in estimation (Tintner 1944, Heady 1946). Diminishing marginal returns to capital, for example, is validated by taking the second partial derivative of output with respect to capital, $(\partial^2 Y)/(\partial C^2) = A\beta_1(\beta_1 - 1)C^{\beta_1 - 2} L^{\beta_2} D^{\beta_3}$, which will always be negative as long as all variables are positive and β_1 is a positive fraction. The unrestricted C-D additionally allows for simple testing of industry returns to scale. If the sum of the factor elasticities is equal to one , $\beta_1 + \beta_2 + \beta_3 = 1$, then the industry is experiencing constant returns to scale , if the elasticities sum to greater than one, $\beta_1 + \beta_2 + \beta_3 > 1$, it is facing increasing returns to scale, and if less than one, $\beta_1 + \beta_2 + \beta_3 < 1$, decreasing returns to scale (Bronfenbrenner and Douglas 1939). Among the accepted limitations of the Cobb-Douglas form is that, by imposing a unitary substitution elasticity, it requires technically complementary factors, frequently resulting in issues of multicollinearity among inputs (Doll 1974).

Technical Efficiency

Management is absent from this simple model mostly because this factor is notoriously difficult to observe in a measurable way. Tintner (1944), Tintner and Brownlee (1944) and Heady (1946) all note that the absence of management is an obvious weakness not easily overcome. By excluding management, the input quantities and proportions are assumed to be ideal management decisions that maximize output, and any variation, or error, in the execution of these decisions is assumed part of the random error term (Smith 1945). Griliches (1957b) argues that omission of a relevant variable measuring managerial or entrepreneurial ability will bias returns to scale downward and returns to capital upward. Marschak and Andrews (1944) relate random differences between firms in the same industry to the "technical knowledge, the will, effort, and luck of a given entrepreneur" as summarized by unobserved "technical efficiency." Farrell (1957) offers a straightforward measure of technical efficiency following Debreu's (1951) "coefficient of resource utilization."

Along this line of reasoning, managerial ability is related to the efficient use of optimally allocated inputs to maximize output, or the efficiency in execution of a management plan. In theory, there exists a frontier of maximum outputs obtainable from optimal input sets and a given production technology. By relegating factors of management efficiency into a single stochastic error term during regression analysis, all variation is assumed to be randomly and normally distributed about an industry average production function assumed to approximate the actual production frontier. Aigner and Chu (1968) use mathematical programming to model production where an individual firm's output is allowed to deviate from the estimated frontier due both to purely random shocks as well as differences in technical efficiency, thus explicitly allowing firms to fall short of the maximum obtainable output levels. Improving upon the developments since Aigner and Chu to estimate stochastic, parametric production functions that include separate efficiency measures, Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977) independently proposed the now commonly known stochastic frontier production function by assuming the single stochastic error term in linear regression models is in fact composed of two independent sources of disturbance, one from true stochastic noise and one from operating inefficiency.

A short derivation of the stochastic frontier model is presented here following the literature accompanying the statistical software used in analysis (Statacorp 2009a). Given the production function for firm $i = 1, \ldots, N$ as $Y_i = f(\mathbf{X}_i, \boldsymbol{\beta})$, the production function for firm *i* with the potential to produce less than efficient output is $Y_i = f(\mathbf{X}_i, \boldsymbol{\beta})\xi_i$, where ξ_i is bound by the interval (0,1]. A perfectly efficient firm will operate where $\xi_i = 1$, and inefficient firms will operate where $0 < \xi_i < 1$, thus producing only a fraction of the maximum output obtainable given the same input combination and technology. A production function for a firm that has potential for inefficiency and is subject to random shocks is written as $Y_i = f(\mathbf{X}_i, \boldsymbol{\beta})\exp(v_i)\xi_i$. Assuming the production technology is of the Cobb-Douglas form, the frontier production function is linear in logs with k inputs and written as $\ln(Y_i) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(X_{ji}) + v_i + \ln(\xi_i)$. Simplifying notation,

$Y_i = \mathbf{X}_i\boldsymbol{\beta} + v_i - u_i$ where u_i is defined as $-\ln(\xi_i)$ and restricted by $u_i \geq 0$ ensuring $0 < \xi_i \leq 1$.

The symmetric stochastic disturbance term is assumed to have an independent and identically distributed normal distribution, $\nu_i \sim \text{iid}.N(0, \sigma_v^2)$, while the inefficiency term is typically of a half-normal or exponential distribution as recommended by Meeusen and van den Broeck (1977), although other distributions have been used. Technical efficiency ($\xi_i = TE_i$) is measured as actual output relative to the potential output defined by the production frontier, $TE_i = \exp(\mathbf{X}_i\boldsymbol{\beta} - u_i)/\exp(\mathbf{X}_i\boldsymbol{\beta}) = \exp(-u_i)$, which is the Debreu-Farrell single-output, output-oriented measure of technical efficiency. The *TE* of an efficient producer will equal 1 while any producer below the frontier will have a *TE* between 0 and 1, producers with values closer to 1 being more efficient (Coelli, Prasada Rao, and Battese 1998).

Weather as Agricultural Input

The production function developed so far exludes exogenous weather variables, W, that affect the production environment. Stallings (1961), Shaw (1964), Oury (1965), and Doll (1967) focus attention on identifying practical measures of weather that can be effectively used in economic analyses, defined by Doll simply as "meteorological phenomena affecting yields during a growing season." Yet, just as for management, it is questionable how such a measure would fit within economic production theory and econometric models of production. Oury (1965) proposes including a single normal-weather index directly into the conventional C-D production function as an additional input with presumably similar diminishing marginal productive properties. Similar to that suggested by Oury, a positive weather index of soil humidity at seeding and at tasseling is used by de Janvry (1972) along with soil quality, plant density and fertilizer rate to estimate a per-hectare nitrogen yield response model of a C-D form for corn in Argentina.

Hansen (1991) includes agricultural inputs and production practices with observed weather variables in a tobit model to estimate a generalized yield function for a random sample of field-level yield observations across ten major corn producing states. Hansen found that yields are significantly sensitive to current season variations in weather. Kaufmann and Snell (1997) integrate weather with socio-economic determinants of production, yet the authors clearly note that this model is not an explicit production function with climate variables included, citing unobserved factor inputs and difficulties in assuming physiological optimums and interpreting marginal products of nonlinear weather impacts. Eckaus and Tso (1999) explicitly estimate an agricultural production function for Chinese prefectures using climate variables to control for the growing environment within a C-D framework.

In a conventional production function, weather is typically unobserved and assumed random across observations, thus weather impacts are grouped within the stochastic error term with zero expected mean in estimation. By observing actual variation in weather variables, especially variables with a known relationship with yield, the size of the error is reduced. Assuming that weather is measured as an index with deviations from normal in both directions and with potentially nonlinear impacts, a stochastic C-D production function including weather as an explanatory factor of production beyond producers' control can be written in exponential form as $Y_i =$

$e^{\alpha_0} C_i^{\beta_{i1}} L_i^{\beta_{i2}} D_i^{\beta_{i3}} e^{\gamma_{i1} W_i + \gamma_{i2} W_i^2} e^{\varepsilon_i}$ and in logarithmic form as $\ln Y_i = \alpha_0 + \beta_{i1} \ln C_i + \beta_{i2} \ln L_i + \beta_{i3} \ln D_i + \gamma_{i1} W_i + \gamma_{i2} W_i^2 + \varepsilon_i$. This approach to including exogenous random weather inputs is equally applicable in a stochastic frontier framework as long as the variables are assumed to impact only the environment in which production occurs and are thus a part of firm heterogeneity affecting output only and not producer inefficiency (Kumbhakar and Lovell 2000, Greene 2008b). The stochastic C-D production function frontier in log form—with weather variables now included—would be $\ln Y_i = \alpha_0 + \beta_{i1} \ln C_i + \beta_{i2} \ln L_i + \beta_{i3} \ln D_i + \gamma_{i1} W_i + \gamma_{i2} W_i^2 + v_i - u_i$, which serves as the basis for econometric models estimated below.

Estimation Method

Maximum likelihood estimation is preferred for stochastic frontier analysis since the distribution of the composed error term is assumed non-normal by inclusion of an additional error term capturing the one-sided inefficiency effect. The maximum likelihood method of estimation is a general approach shown to produce best, linear, unbiased estimators (BLUE) identical to ordinary least squares (OLS) estimators under the classical linear model assumptions. Yet, the maximum likelihood method is more flexible than OLS because it also allows efficient estimation of models with relaxed distributional assumptions on the stochastic error terms by basing analysis directly on the observed distribution of the dependent variable conditional on the explanatory variables (Wooldridge 2009). The conditional joint density function of the dependent variable, $\prod f(Y_i | \mathbf{X}_i, \boldsymbol{\beta})$, describes the likelihood of observing the given sample. The maximum likelihood estimate (MLE) for $\boldsymbol{\beta}$ is obtained by first converting the conditional likelihood function by the natural logarithm, then maximizing the log-likelihood function with respect to the parameters, including the distributional prarmeters of the inefficiency term, $\max_{\boldsymbol{\beta}} \sum \ln L = \max_{\boldsymbol{\beta}} \sum \ln f(Y_i|\mathbf{X}_i, \boldsymbol{\beta})$. The MLE, in the simplest sense, is the optimal value that solves the first order conditions for a local maximum of the log-likelihood function (Greene 2008a).

The log-likelihood function to be maximized for a stochastic frontier model with a normally distributed symmetric error term and an exponentially distributed, one-sided inefficiency term can be written as $\ln L = \sum_{i=1}^{N} \{-\ln \sigma_u - \ln (\sigma_v/2\sigma_u^2) + \ln\Phi(\{-\varepsilon_i - (\sigma v2/\sigma u\ )\ \}/\sigma v\ -\varepsilon i/\sigma u$ where $\sigma v2$ is the variance of the error term, $\sigma u2$ is the variance of the inefficiency term, $\varepsilon_i = Y_i - f(\mathbf{X}_i, \boldsymbol{\beta})$, and $\Phi()$ is the cumulative distribution function of the standard normal distribution. A simple way to test for the presence of inefficiency is to compare the magnitudes of the estimated error variances. If σ_u^2 is significantly larger than σ_v^2, the variation in yield due to inefficiency dominates the variation due to random noise, which signifies inefficiency in the industry (Aigner, Lovell and Schmidt 1977; Meeusen and van den Broeck 1977). An estimate for the inefficiency error term is obtained from the mean of the conditional distribution, $f(u|\varepsilon_i) = \mu_i + \sigma_v\{\phi(-\mu_i/\sigma_v)/\Phi(\mu_i/\sigma_v)\}$. Technical efficiency, following the derivation of the frontier model presented above, is then estimated by $TE_i = E\{\exp(-u_i)|\varepsilon_i\} = \{(1 - \Phi(\sigma_v - \mu_i/\sigma_v))/(1 - \Phi(-\mu_i/\sigma_v))\}\exp(-\mu_i + \sigma_v^2/2)$ where $\mu_i = \varepsilon_i - \sigma_v^2/\sigma_u$ for the normal-exponential specification (Statacorp 2009a).

IV. Data

Corn Production Data

Corn production data are collected from the United States Department of Agriculture's (USDA) Agricultural Resource Management Survey (ARMS), administered annually for specified crops by the USDA National Agricultural Statistics Service (NASS) and Economic Research Service (ERS). The Phase 2: Production Practices and Costs Report for corn producers for the years 1996, 2001, 2005 and 2010 was accessed by permission as a temporary Special Sworn Data User through a secure Data-Lab in the local NASS field office. The ARMS is a non-random survey that uses a complex multi-phase, multi-frame, stratified, probability-weighted sampling design, with the final sampling unit for the Phase 2 corn survey being a randomly selected corn field within a selected farm operation's total planted corn acreage. Each selected farm represents a specified number of other similar farms classified by particular characteristics such as farm type, land use, and size class for that year. Each year's sample represents an independent, weighted cross-section of the total U.S. corn farm population (Ebel and Vasavada 2009). Through inspection there was found to be no apparent relationship between the size of the randomly selected field and an operation's total corn acreage or total operation size, so appropriate variables were constructed as per-acre values in order to estimate the technical production relationships between comparable production units.

Table 1 shows the sample size and represented farm population as well as the number of observations and the percent of the total population represented within each seed technology group categorized above. Observations are additionally grouped according to their location within an ERS Farm Resource Region (FRR), with all observations West of the Heartland and all observations South or East of the Heartland collected into two groups because of limited observations in separate FRR in these areas. It is evident that use of conventional, non-GE seed technology has dropped significantly while adoption of stacked-trait seed technology has increased, especially after 2005. Adoption of HRV and IRV alone leveled off after initial adoption as these traits were combined within STK. The low number of observations in alternative seeds in 1996 prevents reliable comparisons within this year, and the difference in available traits available within the currently popular STK varieties in 2001 limit the usefulness of comparisons for this year, so analysis and interpretation is focused on the years 2005 and 2010 in which the level of adoption is higher and the available traits are most similar.

Table 1. Sample and percent of represented population by region and seed variety.

	1996		2001		2005		2010	
Starting Sample	1,379		2,930		2,159		2,692	
Usable Sample	1,339		2,404		1,794		1,901	
Starting Population	2,081,858		1,961,281		1,904,413		1,764,934	
Final Population	1,955,651		1,529,373		1,600,345		1,496,733	
Non-GE (**NON**)	1239	**95.7%**	1676	**69.4%**	686	**46.5%**	271	**14.6%**
Herbicide Resistant (**HRV**)	76	**2.6%**	209	**7.1%**	420	**16.1%**	427	**17.1%**
Insect Resistant (**IRV**)	24	**1.7%**	452	**20.3%**	489	**28.5%**	351	**19.4%**
Stacked HRV + IRV (**STK)**	---	---	67	**3.2%**	199	**8.9%**	852	**48.9%**
Heartland (**HART**)	633	**53.4%**	1241	**56.40%**	816	**59.20%**	935	**54.6%**
NON	605	51.7%	880	40.3%	555	28.4%	141	7.8%
HRV	18	1.2%	91	3.2%	121	6.5%	120	5.8%
IRV	10	0.5%	243	11.4%	252	18.6%	187	11.2%
STK	---	---	27	1.6%	88	5.7%	487	29.8%
Northern Crescent (**NRTH**)	305	**28.9%**	394	**26.5%**	341	**23.5%**	312	**25.2%**
NON	293	27.9%	276	17.4%	160	12.8%	70	4.9%
HRV	3	0.1%	27	2.1%	75	4.5%	91	5.9%
IRV	9	1.0%	70	5.9%	82	5.0%	36	3.5%
STK	---	---	18	1.0%	24	1.2%	115	10.9%
Western Regions (**WEST**)	185	**7.8%**	555	**11.0%**	440	**12.2%**	447	**13.9%**
NON	175	7.6%	340	6.5%	90	3.0%	27	0.9%
HRV	9	0.1%	72	1.3%	153	3.6%	122	3.0%
IRV	1	< 0.1%	125	2.7%	123	3.8%	95	3.4%
STK	---	---	18	0.5%	74	1.8%	203	6.5%
East/South Regions (**EAST**)	216	**9.9%**	214	**6.1%**	197	**5.1%**	207	**6.4%**
NON	166	8.5%	180	5.1%	81	2.2%	22	1.0%
HRV	46	2.6%	19	0.6%	71	1.5%	94	2.4%
IRV	4	0.1%	14	0.3%	32	1.2%	33	1.2%
STK	---	---	1	0.1%	13	0.2%	47	1.8%

As a way to survey the general economic structure of the corn industry over this period, table 2 presents per-acre average cost figures estimated from field level reports for major physical inputs, expanded to represent all U.S. farms using the provided probability weights. Fertilizer costs (Fert) have risen similarly for each seed type and region. Seed costs (Seed) have risen more than fertilizer costs for all seed types, and seed costs are highest for STK. Not surprisingly, all costs are highest in the Heartland regions where input demand is largest. There are two additional, interesting observations to note. First, increases in costs for seed and fertilizer are dramatic between 2005 and 2010 as compared to previous period increases, which is likely due to the jump in farm prices paid associated with the food price crisis noted above. And second, average per-acre costs for chemical pesticide inputs (Chem) remained about the same over the whole period. This trend may be the result of cost savings related to the pest damage control provided by GE technologies as well as changes to other pest control practices associated with these technologies.

Table 3 totals these input costs and subtracts them from estimated per-acre value of production calculated from average per-acre yields and regional average corn prices to derive a simplified value for per-acre profit. Several trends are immediately visible. For example, yields increase as regions approach the Heartland and as seed varieties approach STK. As expected, the highest yields are obtained on corn farms in the Heartland that adopt stacked GE seed technologies. More interesting are the changes in value of production and the resulting changes in profit. As seen in figure 1c above, the per-bushel price for grain corn was experiencing a drop from 1996 to about 2001, and remained low in 2005. This translates into a dip in the value of production despite

Table 2. Seed, fertilizer and chemical input costs per acre across seed variety, region and year in nominal (n) and real (r) dollars[A]

			NON				**HRV**				**IRV**				**STK**				**ALL VARIETIES**			
			1996	2001	2005	2010	1996	2001	2005	2010	1996	2001	2005	2010	1996	2001	2005	2010	1996	2001	2005	2010
HART	Seed	(n)	$76	$85	$87	$150	$74[C]	$96	$98	$160	$88[C]	$110	$99	$186	-	$110	$119	$196	$76	$89	$95	$183
		(r)	**$87**	**$112**	**$146**	**$464**	**$85**	**$127**	**$165**	**$495**	**$102**	**$145**	**$166**	**$577**	-	**$145**	**$201**	**$607**	**$87**	**$118**	**$160**	**$569**
	Fert	(n)	$51	$52	$67	$108	$41	$46	$64	$101	$49	$49	$58	$98	-	$37	$51	$105	$50	$51	$62	$104
		(r)	**$63**	**$64**	**$110**	**$272**	**$50**	**$57**	**$104**	**$254**	**$61**	**$60**	**$95**	**$248**	-	**$46**	**$84**	**$264**	**$63**	**$63**	**$102**	**$261**
	Chem	(n)	$28	$28	$26	$26	$32	$23	$21	$21	$41	$27	$27	$22	-	$25	$16	$25	$29	$27	$25	$24
		(r)	**$33**	**$33**	**$32**	**$37**	**$37**	**$28**	**$26**	**$30**	**$48**	**$33**	**$34**	**$32**		**$31**	**$20**	**$35**	**$33**	**$33**	**$31**	**$34**
NRTH	Seed	(n)	$72	$81	$89	$134	$87[B]	$95	$99	$167	$78[B]	$109	$101	$183	-	$109[C]	$126	$197	$72	$87	$95	$176
		(r)	**$82**	**$107**	**$150**	**$417**	**$100**	**$125**	**$166**	**$519**	**$90**	**$144**	**$169**	**$566**	-	**$144**	**$212**	**$611**	**$83**	**$114**	**$160**	**$545**
	Fert	(n)	$36	$41	$45	$69	$66	$30	$53	$69	$26	$47	$45	$94	-	$64	$56	$84	$36	$43	$47	$79
		(r)	**$45**	**$51**	**$73**	**$173**	**$82**	**$37**	**$87**	**$173**	**$32**	**$58**	**$75**	**$236**	-	**$79**	**$92**	**$210**	**$45**	**$52**	**$77**	**$198**
	Chem	(n)	$26	$26	$19	$20	$27	$20	$19	$24	$15	$31	$22	$23	-	$22	$21	$21	$26	$27	$20	$22
		(r)	**$31**	**$32**	**$24**	**$29**	**$32**	**$25**	**$24**	**$34**	**$18**	**$37**	**$27**	**$33**	-	**$27**	**$26**	**$31**	**$31**	**$32**	**$24**	**$31**
WEST	Seed	(n)	$76	$84	$93	$177	$82[B]	$91	$103	$147	$110[B]	$112	$101	$167	-	$112[C]	$110	$174	$76	$90	$101	$166
		(r)	**$88**	**$111**	**$155**	**$549**	**$94**	**$120**	**$174**	**$455**	**$127**	**$148**	**$170**	**$517**	-	**$148**	**$185**	**$539**	**$88**	**$119**	**$170**	**$516**
	Fert	(n)	$36	$39	$47	$46	$41	$32	$38	$46	$43	$39	$55	$73	-	$40	$45	$78	$37	$38	$47	$68
		(r)	**$45**	**$48**	**$77**	**$116**	**$51**	**$39**	**$62**	**$117**	**$54**	**$48**	**$91**	**$185**	-	**$49**	**$73**	**$197**	**$45**	**$47**	**$76**	**$171**
	Chem	(n)	$22	$24	$17	$15	$27	$16	$12	$19	$17	$26	$19	$23	-	$22	$14	$23	$22	$24	$16	$21
		(r)	**$26**	**$30**	**$21**	**$22**	**$32**	**$20**	**$15**	**$28**	**$20**	**$32**	**$24**	**$33**	-	**$27**	**$17**	**$32**	**$26**	**$29**	**$19**	**$31**
EAST	Seed	(n)	$68	$84	$85	$107	$71	$94[C]	$94	$136	$63[B]	$90[C]	$94	$150	-	$90[B]	$121[C]	$166	$68	$86	$91	$142
		(r)	**$78**	**$111**	**$143**	**$331**	**$82**	**$125**	**$158**	**$421**	**$72**	**$119**	**$158**	**$466**	-	**$119**	**$203**	**$513**	**$78**	**$113**	**$154**	**$442**
	Fert	(n)	$52	$48	$53	$81	$55	$46	$61	$99	$62	$62	$57	$102	-	$61	$25	$104	$52	$49	$55	$98
		(r)	**$64**	**$59**	**$87**	**$204**	**$68**	**$57**	**$101**	**$249**	**$76**	**$77**	**$93**	**$257**	-	**$75**	**$41**	**$262**	**$65**	**$60**	**$91**	**$247**
	Chem	(n)	$27	$24	$24	$21	$25	$31	$18	$26	$36	$24	$21	$23	-	$27	$15	$20	$26	$24	$21	$23
		(r)	**$31**	**$29**	**$31**	**$31**	**$29**	**$37**	**$23**	**$37**	**$42**	**$30**	**$26**	**$33**	-	**$32**	**$18**	**$29**	**$31**	**$30**	**$26**	**$33**
ALL REG	Seed	(n)	$74	$84	$88	$143	$73	$95	$99	$157	$81	$109	$99	$180	-	$109	$118	$192				
		(r)	**$85**	**$110**	**$147**	**$445**	**$84**	**$125**	**$167**	**$486**	**$93**	**$144**	**$167**	**$557**	-	**$144**	**$199**	**$596**				
	Fert	(n)	$45	$48	$59	$89	$48	$39	$55	$80	$36	$47	$56	$93	-	$47	$50	$97				
		(r)	**$56**	**$59**	**$97**	**$224**	**$60**	**$48**	**$90**	**$201**	**$45**	**$58**	**$91**	**$235**	-	**$58**	**$82**	**$243**				
	Chem	(n)	$27	$27	$24	**$23**	$28	$22	$18	$22	$25	$28	$25	$22	-	$24	$16	$23				
		(r)	**$32**	**$32**	**$29**	**$33**	**$33**	**$26**	**$23**	**$32**	**$29**	**$34**	**$31**	**$32**	-	**$29**	**$20**	**$34**				

[A] Real dollar values calculated from separate USDA NASS annual farm prices paid indices for seed, fertilizer and chemical inputs for respective years (base 1990-1992).
[B] Values in this year/region column estimated from less than 10 sample observations.
[C] Values in this column estimated from less than 20 but at least 10 sample observations.

Table 3. Yield, value, cost and profit per acre across seed variety, region and year in nominal (n) and real (r) dollars[A].

			NON				HRV				IRV				STK				ALL VARIETIES			
			1996	2001	2005	2010	1996	2001	2005	2010	1996	2001	2005	2010	1996	2001	2005	2010	1996	2001	2005	2010
HART	Yield	**bu**	**134**	**147**	**143**	**145**	**119[C]**	**136**	**155**	**146**	**143[C]**	**149**	**158**	**160**	-	**138**	**155**	**168**	**134**	**147**	**150**	**161**
	Value	(n)	$368	$291	$287	$796	$325	$268	$311	$804	$392	$295	$316	$879	-	$273	$311	$924	$367	$290	$301	$884
		(r)	**$578**	**$264**	**$319**	**$1401**	**$510**	**$244**	**$345**	**$1415**	**$615**	**$269**	**$351**	**$1547**	-	**$248**	**$346**	**$1627**	**$577**	**$264**	**$334**	**$1556**
	Cost	(n)	$155	$165	$180	$283	$147	$165	$184	$281	$179	$186	$184	$306	-	$172	$187	$325	$155	$168	$182	$311
		(r)	**$183**	**$210**	**$288**	**$772**	**$173**	**$212**	**$296**	**$779**	**$211**	**$238**	**$295**	**$856**	-	**$221**	**$304**	**$907**	**$183**	**$214**	**$293**	**$864**
	Profit	**(r)**	**$394**	**$55**	**$31**	**$629**	**$337**	**$33**	**$49**	**$637**	**$405**	**$30**	**$56**	**$691**	-	**$27**	**$41**	**$719**	**$393**	**$50**	**$42**	**$692**
NRTH	Yield	**bu**	**126**	**110**	**141**	**130**	**105[B]**	**140**	**134**	**154**	**129[B]**	**131**	**154**	**160**	-	**121[C]**	**153**	**162**	**127**	**117**	**143**	**154**
	Value	(n)	$351	$217	$284	$713	$291	$276	$268	$845	$359	$259	$308	$878	-	$238	$306	$890	$351	$232	$287	$843
		(r)	**$551**	**$198**	**$315**	**$1255**	**$456**	**$251**	**$298**	**$1488**	**$563**	**$236**	**$342**	**$1546**	-	**$217**	**$340**	**$1566**	**$551**	**$211**	**$319**	**$1484**
	Cost	(n)	$134	$148	$153	$223	$180	$145	$171	$260	$119	$187	$168	$299	-	$196	$203	$302	$134	$156	$152	$276
		(r)	**$158**	**$189**	**$246**	**$619**	**$214**	**$186**	**$277**	**$726**	**$139**	**$239**	**$270**	**$836**	-	**$250**	**$330**	**$852**	**$158**	**$199**	**$262**	**$775**
	Profit	**(r)**	**$393**	**$8**	**$68**	**$636**	**$243**	**$65**	**$21**	**$762**	**$424**	**-$3**	**$72**	**$711**	-	**-$33**	**$10**	**$714**	**$393**	**$12**	**$57**	**$710**
WEST	Yield	**bu**	**123**	**131**	**115**	**131**	**112[B]**	**98**	**107**	**110**	**91[B]**	**149**	**159**	**134**	-	**139[C]**	**120**	**143**	**123**	**132**	**127**	**133**
	Value	(n)	$333	$262	$235	$681	$301	$197	$219	$571	$245	$298	$326	$694	-	$278	$247	$746	$332	$264	$260	$691
		(r)	**$522**	**$238**	**$261**	**$1198**	**$472**	**$179**	**$243**	**$1005**	**$385**	**$271**	**$362**	**$1222**	-	**$253**	**$274**	**$1313**	**$521**	**$240**	**$289**	**$1216**
	Cost	(n)	$135	$147	$157	$238	$150	$139	$153	$213	$170	$177	$176	$263	-	$174	$169	$274	$135	$152	$164	$256
		(r)	**$159**	**$188**	**$254**	**$687**	**$177**	**$178**	**$251**	**$600**	**$200**	**$227**	**$285**	**$735**	-	**$224**	**$276**	**$768**	**$159**	**$195**	**$266**	**$718**
	Profit	**(r)**	**$363**	**$50**	**$7**	**$511**	**$295**	**$1**	**-$7**	**$405**	**$185**	**$44**	**$77**	**$488**	-	**$29**	**-$2**	**$545**	**$361**	**$45**	**$23**	**$498**
EAST	Yield	**bu**	**105**	**117**	**119**	**114**	**84**	**124[C]**	**107**	**960**	**104[B]**	**131[C]**	**104**	**115**	-	**100[B]**	**119[C]**	**105**	**102**	**131**	**112**	**105**
	Value	(n)	$356	$262	$265	$589	$285	$277	$240	$495	$351	$293	$232	$592	-	$224	$276	$540	$347	$294	$250	$541
		(r)	**$559**	**$238**	**$295**	**$1,037**	**$448**	**$252**	**$266**	**$872**	**$551**	**$267**	**$258**	**$1,043**	-	**$204**	**$306**	**$950**	**$545**	**$268**	**$278**	**$952**
	Cost	(n)	$146	$156	$162	$209	$151	$171	$174	$261	$160	$177	$172	$276	-	$178	$161	$290	$147	$159	$168	$264
		(r)	**$173**	**$198**	**$260**	**$565**	**$179**	**$218**	**$281**	**$707**	**$191**	**$225**	**$277**	**$757**	-	**$226**	**$263**	**$804**	**$174**	**$202**	**$270**	**$722**
	Profit	**(r)**	**$386**	**$40**	**$35**	**$472**	**$269**	**$33**	**-$15**	**$165**	**$361**	**$41**	**-$19**	**$286**	-	**-$22**	**$43**	**$146**	**$371**	**$65**	**$86**	**$230**
ALL REG	Yield	**bu**	**129**	**134**	**140**	**137**	**102**	**129**	**134**	**136**	**131**	**144**	**155**	**153**	-	**131**	**147**	**161**				
	Value	(n)	$367	$278	$290	$729	$290	$268	$278	$721	$376	$299	$321	$812	-	$273	$305	$858				
		(r)	**$577**	**$253**	**$322**	**$1283**	**$455**	**$244**	**$308**	**$1269**	**$590**	**$272**	**$357**	**$1428**	-	**$248**	**$339**	**$1511**				
	Cost	(n)	$147	$158	$170	$255	$150	$155	$172	$259	$142	$185	$180	$296	-	$180	$185	$312				
		(r)	**$173**	**$202**	**$273**	**$702**	**$177**	**$199**	**$279**	**$719**	**$167**	**$236**	**$289**	**$825**	-	**$231**	**$301**	**$873**				
	Profit	**(r)**	**$404**	**$51**	**$49**	**$581**	**$278**	**$45**	**$29**	**$550**	**$423**	**$35**	**$68**	**$604**	-	**$17**	**$38**	**$638**				

[A] Nominal value of yield calculated from region average price paid per bushel. Real values calculated from USDA NASS annual food grain prices received and paid indices. (sources: http://quickstats.nass.usda.gov/ and http://usda.mannlib.cornell.edu/MannUsda/homepage.do/)
[B] Values in this year/region column estimated from less than 10 sample observations. [C] Values in this column estimated from less than 20 but at least 10 sample observations.

continued increases in yield. With costs for inputs rising over the same period, the resulting economic return to farming corn was falling. Profits were negative in 2001 for several regions and seed varieties. Considering the simplicity of the cost estimate provided—in that it excludes all costs associated with production other than seed, fertilizers and pesticides—it is reasonable to assume that many corn farms were not profitable from corn production alone over these years. Yet, the incredible rise in the price of corn in succeeding years more than compensated for any cost increases, leading to highly profitable corn farming in 2010.

Drought Data

Although annual cumulative moderate heat and cumulative high heat variables are now standard in yield function specifications, these observations are not currently readily available for the entire region of interest in this study. Additionally, the present focus is on drought specifically, for which index variables are freely available and easily obtained. Seasonal drought conditions are incorporated using Palmer's Moisture Anomaly "Z-index" (Z) recorded monthly by the United States Department of Commerce (USDOC) National Oceanic and Atmospheric Administration (NOAA) National Climate Data Center (NCDC) by climate division. Historical values for the months of June, July and August were accessed through NOAA's National Environmental Satellite, Data, and Information Service (NESDIS) Climate Data Online (CDO) web portal[11]. NCDC Climate Divisions correspond to USDA Crop Reporting Districts (CRD)[12] which cluster counties

[11] Available at http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#
[12] Division and district boundaries differ only slightly for very few divisions after CRD remapping in 2007.

into no more than 10 divisions within each state according to similar local climate patterns.

The Z-index is a computationally complex meteorological index that incorporates cumulative precipitation, evapotranspiration, and soil-moisture into a single measure of deviations from local climatic averages as an indicator of relative dryness or moisture, providing a direct, standardized comparison of differences from normal divisional climate conditions (Alley 1985). The Z-index differs from the PDSI by measuring variation from individual monthly norms independent of cumulative conditions from prior months, making it preferable for use in agricultural studies involving time-specific phenological stages of development over a single season. (Karl 1986). Normal conditions are indicated by a Z of zero, with mid-range average conditions varying from -1.24 to +.99. Dry conditions increase as the values move below zero, with severe drought indicated by $Z < -2$. Moisture increases as the Z-index increases greater than zero, with very moist conditions indicated by $Z > +2.5$.

For ease of interpretation, the sign of each value is inverted during esimation so that positive Z values correspond to dry conditions. This allows negative coefficient estimates for the linear Z term to be interpreted as the result of a negative impact of increasingly dry conditions on yield. A negative coefficient estimate for the quadratic Z term can be interpreted as the result of a concave functional relationship between the Z-index and per-acre yield, with the Z-index impact becoming increasingly negative as the Z term moves away from an optimum in either direction. Three monthly drought indexes are included separately to capture the impact of conditions immediately before, during, and immediately after the tasseling stage of corn development, with the most consistent and significant impact expected for the peak tasseling month of July.

Since multiple counties are clustered within a single Z-index observational unit, there is a higher likelihood that farms are randomly distributed within each drought observation. When these farms employ different production practices and adopt different seed technologies, there exists a natural experiment comparing technical, input-output relationships within identical production environments. It is assumed that the nature of the clustered variable as well as the relatively large number of clusters of relatively small size reduces the errors typically associated with clustered linear models (Wooldridge 2003). Also, since the clustered observation is a continuous variable measure of a known environmental condition in a division rather than a valueless group category, the state of each observation is observed and it is only the impact of this state that is to be estimated. The cluster is not a unit of space or time with unknown fixed or random effects to be estimated.

Variable Description

The ARMS contains detailed information about the production practices and input quantities for each field-level observation. Since the primary objective of this study is to observe the interaction of alternative seed technologies with drought variables, effort was made to simplify the production model by selecting only those physical input variables that are expected to directly and significantly affect yield. This effort was aided by the relatively homogenous nature of the U.S. corn industry and the limited availability of certain traditionally included input variables.

For instance, the two most conventional factors of production are capital and labor. Yet, for U.S. industrialized agriculture, with relatively uniform, capital intensive practices across all major corn growing regions, significant variation in related, available values such as number of field passes with machinery or hours spent in labor other than machinery operation is not observed. In fact, a majority of producers reported zero hours of field labor for additional tasks such as pest scouting or rock picking. Preliminary regressions that included number of field passes with machinery and number of additional labor hours—employing a dummy for observations with zero values, following Battese (2008)—showed mixed results with frequently insignificant and/or negative estimates for these variables. Proxies for these inputs in the form of values of machinery and labor used in production were not available at the field level in the Phase 2 report.

Quantity of land is another conventional agricultural input. When describing total farm output by total capital, labor and land used in production, land quantity is expected to show diminishing marginal returns holding other factors constant. Also, land quality is expected to diminish with increased total quantity according to Ricardian rent theory (Ricardo 1821). By weighting output and inputs by land quantity, creating per-acre values, the factor elasticity of production for land is not estimated. This omission is overcome by including the agronomically relevant variable "yield goal," as recorded in the ARMS report, as the primary determinant of actual yield. Yield goal is an industry-wide measure of field-specific per-acre yield expectations based upon an upward projection from a recent, high-yield average (Miller 1986; Dahnke et al. 1988). Yield goal is determined prior to planting, then used along with soil tests to help assess current season nutrient management needs (Chang et al. 2004).

Although there may exist slight differences in the preferred method to determine a realistic yield goal or in the emphasis farmers put into this measure, it is assumed that these differences are captured within the idiosyncratic error term. Variation in stated yield goal between observations captures field specific land quality as well as farmer specific historical production habits. Preliminary regressions including yield goal with detailed accounts for pounds of applied nitrogen, potassium, and phosphorous resulted in yield goal absorbing any significance previously associated with fertilizer use. The only other continuous variable included with yield goal is seeding rate. In this model of production, seed rate is envisioned as the working capital variable since seeds are the natural machinery which convert available radiation, nutrients and water into the desired agricultural product. Yield goal explains the relative availability of resources—mostly due to inherent land quality but also due to additional physical inputs applied—used by the seed during production. Finally, a dummy variable for irrigation use is included instead of irrigation rate, since less than five percent of farms on average employed any irrigation in regions other than WEST.

The four seed variety groups cited above are used to categorize producers by production technology. With conventional seed varieties (NON) excluded as the base technology, herbicide resistant varieties (HRV), insect resistant varieties (IRV) and herbicide resistant and insect resistant varieties stacked (STK) are modeled as intercept shifting alternative technologies in the national industry model. Separate regional dummies were also created for the Northern Crescent region (NRTH), the Western regions (WEST) and the Eastern regions (EAST)—with the Heartland (HART) as base—to capture regional differences in production environment that might influence yield.

Population weighted mean values for production variables are presented in table 4. Irrigation rate is included to show average inches of irrigation for those farms using irrigation. The pre-planting yield goal is on average 5 to 15 percent larger than the average per-acre yield observed. This supports the usefulness of yield goal in capturing field-specific fertility and production practices: farmers will project realistic yield goal values consistent with past experience, thus a field with poor soil or with productive soils will not be projected to yield more than a measured percentage above what is possible under optimal conditions. Average seeding rate is closer to 30 thousand kernels per acre for HART and NRTH, and closer to 25 thousand kernels per acre for WEST and EAST. Seeding rate also appears to increase in HART and NRTH as seed technology moves from NON to STK, especially in 2010. The percent of fields using irrigation is highest in the WEST and the seed variety that receives the largest amount of water on average when irrigation is applied is HRV. It is also clear that HART and NRTH had more farms using irrigation at higher rates on average in 2005 than in 2010.

Sample summary statistics for June, July and August Z-index terms for 2005 and 2010 are grouped by region and seed variety in table 5. Noting that the sign of the Z-index has been inverted, negative mean values reflect wetter conditions while positive mean values reflect dryer conditions. The first and most important observation to be made is the difference in average July conditions between 2005 and 2010. The 2005 season had a large number of divisions experiencing drought conditions so that the Z term is more evenly distributed about a mean very close to zero. The 2010 season was unusually moist for nearly all divisions with very few experiencing dry conditions during

Table 4. Production variable mean values by year, region and seed variety.

Rego	Variable	2005 NON	2005 HRV	2005 IRV	2005 STK	2005 All	2010 NON	2010 HRV	2010 IRV	2010 STK	2010 All
HART	Yield	143.2	154.8	157.6	155.3	150.1	145.0	146.5	160.1	168.3	161.0
	Yieldgoal	163.3	160.9	165.9	158.2	163.4	165.4	164.6	177.4	183.1	177.4
	Seedrate[A]	28.9	29.6	29.3	29.4	29.1	30.2	30.0	31.1	31.8	31.2
	% IRRIG	1.9	1.4	6.4	2.1	3.3	0.8	0.0	3.9	4.7	3.5
	Irrig. Rate	11.93	10.05	10.96	6.43	10.91	8.72	0.00	7.33	7.86	7.76
NRTH	Yield	141.4	133.8	153.7	152.7	143.1	129.9	154.0	160.0	162.1	153.6
	Yieldgoal	149.4	142.1	158.0	162.3	150.5	142.4	153.8	153.1	164.5	156.1
	Seedrate	28.3	28.1	29.0	30.4	28.5	28.8	29.2	30.9	31.9	30.5
	% IRRIG	2.6	1.7	0.6	7.8	2.2	0.0	[B]0.0	0.0	0.0	[B]0.0
	Irrig. Rate	5.47	8.69	7.81	8.00	6.50	0.00	5.52	0.00	0.00	5.52
WEST	Yield	114.9	107.1	159.4	120.5	127.2	130.9	109.8	133.5	143.4	132.8
	Yieldgoal	132.9	120.8	163.1	138.2	139.5	152.5	117.5	146.9	154.5	144.4
	Seedtrate	24.7	23.5	27.4	24.7	25.2	26.4	23.4	25.4	27.0	25.8
	% IRRIG	28.6	19.8	55.6	17.1	32.7	38.1	8.4	24.6	31.2	25.1
	Irrig. Rate	15.36	16.01	13.57	15.15	14.51	13.27	23.51	12.17	15.01	14.77
EAST	Yield	118.9	107.3	104.0	123.4	112.2	114.1	96.0	114.7	104.5	104.7
	Yieldgoal	131.9	122.9	131.0	127.8	128.9	140.2	135.3	142.1	133.3	136.8
	Seedrate	25.4	23.1	25.0	25.3	24.6	27.1	26.4	26.9	27.7	26.9
	% IRRIG	2.8	2.7	1.6	16.5	3.1	2.3	8.2	3.2	0.8	4.3
	Irrig. Rate	5.00	8.46	2.83	10.51	6.85	5.35	10.89	5.85	4.88	9.40
All	Yield	139.7	133.9	154.9	147.0	---	137.0	135.5	152.5	161.3	---
	Yieldgoal	156.0	143.2	162.7	153.9	---	155.2	148.4	165.4	173.4	---
	Seedrate	28.3	27.2	28.8	28.5	---	29.3	28.0	29.8	31.1	---
	% IRRIG	3.9	5.7	11.8	6.3	---	3.0	2.6	6.8	7.0	---
	Irrig. Rate	12.13	14.46	12.53	11.83	---	12.23	17.99	10.35	12.07	---

[A]Seeding rate is measure in thousand seed per acre. [B]Less than %0.05 of population used irrigation.

any month observed. The mean Z in July is less than -2 for HART, NRTH and WEST regions and less than -1.5 for all seed varieties in 2010.

The second important observation is the relatively even distribution of the mean Z term across all seed varieties in both years. Having Z vary similarly over each seed variety allows comparison of the impact Z has on each technology's yield. The results for 2005 are expected to reveal the different impacts that increasing dry conditions have on corn yield for GE and non-GE corn seed varieties. It is expected that the low number of drought observations in 2010 will result in less significant drought impact estimates, but may instead reveal the impact of abnormally high moisture levels.

Table 5. Summary statistics of modified Z-Index by year, region and seed variety.

		2005					2010				
Reg	Index	obs.	mean	std.dev.	min.	max.	obs.	mean	std.dev.	min.	max.
HART	ZJun	816	0.416	2.058	-4.36	3.81	935	-3.786	2.243	-7.50	2.44
	ZJul	816	0.417	1.190	-2.39	2.96	935	-2.688	3.031	-8.75	3.15
	ZAug	816	-0.649	1.970	-5.16	2.05	935	-0.139	1.909	-4.66	3.07
NRTH	ZJun	341	1.066	1.507	-1.81	3.56	312	-2.554	1.858	-5.7	2.41
	ZJul	341	-0.558	1.482	-3.71	2.45	312	-2.205	2.512	-9.29	2.51
	ZAug	341	1.063	1.456	-2.58	3.40	312	0.063	2.286	-3.69	3.16
WEST	ZJun	440	-2.651	2.894	-8.97	1.91	447	-1.608	2.183	-7.82	1.13
	ZJul	440	-0.023	1.308	-3.92	2.88	447	-2.420	1.374	-8.26	0.57
	ZAug	440	-2.162	1.680	-5.85	2.05	447	-0.824	1.904	-4.63	1.92
EAST	ZJun	197	-0.973	2.516	-5.37	3.44	207	0.557	1.429	-3.05	3.30
	ZJul	197	-0.817	1.988	-5.33	2.38	207	0.720	2.752	-8.20	3.62
	ZAug	197	-0.317	2.026	-4.42	2.42	207	1.184	0.913	-2.06	2.63
Variety	Index	obs.	mean	std.dev.	min.	max.	obs.	mean	std.dev.	min.	max.
NON	ZJun	686	0.466	2.319	-8.97	3.81	271	-2.498	2.563	-7.50	3.30
	ZJul	686	-0.038	1.555	-4.70	2.96	271	-1.587	3.025	-9.29	3.62
	ZAug	686	-0.644	2.151	-5.33	3.40	271	0.338	1.925	-4.66	3.16
HRV	ZJun	420	-1.135	2.913	-8.97	3.71	427	-1.844	2.403	-7.82	3.30
	ZJul	420	-0.162	1.536	-5.33	2.96	427	-1.679	2.783	-8.75	3.62
	ZAug	420	-0.901	2.135	-5.33	3.40	427	-0.152	1.996	-4.66	3.16
IRV	ZJun	489	-0.426	2.496	-8.97	3.81	351	-2.585	2.672	-7.82	3.30
	ZJul	489	0.148	1.368	-4.09	2.96	351	-2.478	2.797	-9.29	3.15
	ZAug	489	-0.445	2.048	-5.85	3.12	351	-0.270	2.070	-4.66	3.16
STK	ZJun	199	-1.454	2.725	-8.97	3.71	852	-3.014	2.426	-7.82	3.30
	ZJul	199	0.005	1.067	-3.92	2.96	852	-2.485	2.685	-9.29	3.62
	ZAug	199	-1.167	2.025	-5.33	3.40	852	-0.194	1.919	-4.66	3.16

Econometric Models

Employing the stochastic frontier production model with composed error term and weather included as an environmental factor of production as specified above, and using the production and drought variables collected, the U.S. national corn industry model to be estimated for the years 2005 and 2010 is Model 1:

$$\ln(yield_i) = \beta_0 constant + \beta_1 \ln(yieldgoal_i) + \beta_2 \ln(seedrate_i) + \beta_3 IRRIG_i$$

$$+\beta_4 HRV_i + \beta_5 IRV_i + \beta_6 STK_i + b_7 NRTH_i + b_8 WEST_i + b_9 EAST_i$$

$$+\beta_{10} ZJun_i^2 + \beta_{11} ZJun_i + \beta_{12} ZJul_i + \beta_{13} ZJul_i^2 + \beta_{14} ZAug_i + \beta_{15} ZAug_i^2$$

$$+v_i - u_i \, ,$$

where NON is the base seed variety and HART is the base region for comparison.

To isolate the impact of changes in the Z-index on the four alternative seed varieties, Model 1 is modified by interacting seed varieties with each month's linear and quadratic Z terms and by restricting the sample to each of the four regions separately for 2005 and 2010 in four variations of Model 2:

$$\ln(yield_i) = \beta_0 constant + \beta_1 \ln(yieldgoal_i) + \beta_2 \ln(seedrate_i) + \beta_3 IRRIG_i$$
$$+\beta_4 HRV_i + \beta_5 IRV_i + \beta_6 STK_i$$
$$+\beta_7 ZJun_i + \beta_8 ZJun_i^2 + \beta_9 ZJul_i + \beta_{10} ZJul_i^2 + \beta_{11} ZAug_i + \beta_{12} ZAug_i^2$$
$$+HRV(\beta_{13} ZJun_i + \beta_{14} ZJun_i^2 + \beta_{15} ZJul_i + \beta_{16} ZJul_i^2 + \beta_{17} ZAug_i + \beta_{18} ZAug_i^2)$$
$$+IRV(\beta_{19} ZJun_i + \beta_{20} ZJun_i^2 + \beta_{21} ZJul_i + \beta_{22} ZJul_i^2 + \beta_{23} ZAug_i + \beta_{24} ZAug_i^2)$$
$$+STK(\beta_{25} ZJun_i + \beta_{26} ZJun_i^2 + \beta_{27} ZJul_i + \beta_{28} ZJul_i^2 + \beta_{29} ZAug_i + \beta_{30} ZAug_i^2)$$
$$+v_i - u_i\ ,$$

where NON is the base seed variety for comparison for $HART, NRTH, WEST,$ and $EAST$ regions and $i = 1,2, \ldots n$ for the n number of farms in each region.

To estimate the within sample technical efficiency of alternative seed varieties and to verify the different impacts the Z-index may have on corn yield for each seed technology, Model 2 is modified by interacting resource regions with each month's linear and quadratic Z terms and by restricting the sample to each of the four seed varieties separately for 2005 and 2010 in four variations of Model 3:

$$\ln(yield_i) = \beta_0 constant + \beta_1 \ln(yieldgoal_i) + \beta_2 \ln(seedrate_i) + \beta_3 IRRIG_i$$
$$+\beta_4 NRTH_i + \beta_5 WEST_i + \beta_6 EAST_i$$
$$+\beta_7 ZJun_i + \beta_8 ZJun_i^2 + \beta_9 ZJul_i + \beta_{10} ZJul_i^2 + \beta_{11} ZAug_i + \beta_{12} ZAug_i^2$$

$$+NRTH(\beta_{13}ZJun_i + \beta_{14}ZJun_i^2 + \beta_{15}ZJul_i + \beta_{16}ZJul_i^2 + \beta_{17}ZAug_i + \beta_{18}ZAug_i^2)$$

$$+WEST(\beta_{19}ZJun_i + \beta_{20}ZJun_i^2 + \beta_{21}ZJul_i + \beta_{22}ZJul_i^2 + \beta_{23}ZAug_i + \beta_{24}ZAug_i^2)$$

$$+EAST(\beta_{25}ZJun_i + \beta_{26}ZJun_i^2 + \beta_{27}ZJul_i + \beta_{28}ZJul_i^2 + \beta_{29}ZAug_i + \beta_{30}ZAug_i^2)$$

$$+v_i - u_i \,,$$

where $HART$ is the base resource region for comparison and $i = 1,2, \dots n$ for the n number of farms using either NON, HRV, IRV, or, STK technology.

IV. Results

Estimation Procedure

Frontier estimation is performed using the frontier command within the statistical software package Stata 11, assuming an exponentially distributed inefficiency term and employing the Broyden-Fletcher-Goldfarb-Shanno (BFGS) log-likelihood maximization algorithm (Statacorp 2009b). Feasible starting values for $\boldsymbol{\beta}$ are estimated coefficients obtained from a linear, "average" stochastic production function with identical specification. The starting value for the parameterized idiosyncratic error variance, $\ln\sigma_v^2$, is the natural log of the square root of the mean of squared error from the estimated average function, and an arbitrarily small positive number, e.g. 0.1, for the parameterized inefficiency error variance, $\ln\sigma_u^2$ (Drukker 2003).

The ARMS probability weights are used to weight each observation during estimation to obtain population representative estimates, and the heteroscedasticity-consistent Huber-White sandwich variance estimator is employed to obtain robust standard errors (Huber 1967; White 1980; Statacorp 2009a). Although Dubman (2000) and Kott (2001) recommend using a delete-a-group jackknife variance estimator for full sample estimation of ARMS data—NASS replicate weights are provided within every ARMS data set—it was found in preliminary regressions that this method does not produce consistent results for sub-sample estimation.

After estimating the largest usable sample for Model 1 by both methods and comparing standard error estimates, differences in estimated standard errors were not clearly biased upward or downward with the Huber-White estimator, and at no time did the difference exceed about 30%. The reduced samples in Model 2 and Model 3 were then estimated by both methods, revealing at times a larger than 80% difference in the estimated standard errors. This difference is believed to arise when a significant number of observations is dropped during sub-sample estimation, making the remaining replicate groups no longer representative as intended and biasing the jackknifed standard error estimates. Thus, the Huber-White sandwich estimator is employed in every model, assuming a random bias of at most 30% exists for sub-sample estimation as well as for the full sample. Additional notation is included in the results tables to mark 85% significance levels to account for potentially upward biased standard errors compared to alternative variance estimation methods.

Model 1 Estimation Results

Maximum likelihood parameter estimates for the Model 1 stochastic frontier production function for 2005 and 2010 are presented in table 6 alongside ordinary least squares estimates of the stochastic "average" production function. For 2005, $\sigma_u^2/\sigma_v^2 = e^{\ln\sigma_u^2}/e^{\ln\sigma_v^2} = e^{-3.036}/e^{-4.438} = 4.063$, and for 2010, $\sigma_u^2/\sigma_v^2 = 5.871$, thus variance of error due to inefficiency dominates the variance of error due to random exogenous factors in both years indicating the presence of inefficiency. When inefficiency exists in the industry, modeling production without accounting for inefficiency can result in upward biased factor elasticity estimates (Meeusen and van de Broeck 1977). The Wald χ^2 (chi2) test statistic is slightly larger and the value that maximizes the pseudo log-likelihood function is slightly smaller for 2005 than for 2010. Results of additional χ^2 tests for joint significance of groups of variables are included in table 7.

The three direct factor inputs of yield goal, seeding rate, and irrigation are statistically significant for 2005 and 2010, with estimated magnitudes slightly larger in 2005. All three seed variety variables (V terms) are significant in 2010, while only one is significant in 2005; two of the three region variables (R terms) are significant in 2010, while only one is significant in 2005; and five of the six Z-index variables (Z terms) are significant in 2005, while three of six are significant in 2010. The effect of changes in the Z-index during the month of July is considered most influential to final corn yield. The sign is negative for the statistically significant linear and quadratic Z terms in 2005, revealing an increasingly negative marginal impact of the relative moisture levels on per-acre corn yield. This relationship, although weaker and less significant, appears to hold for the months of June and August as well.

Table 6. Model 1 average and frontier function estimation results.

Average Function OLS Estimates			Frontier Function ML Estimates		
ln(yield)	2005	2010	ln(yield)	2005	2010
ln(yieldgoal)	0.912***	0.817***	ln(yieldgoal)	0.772***	0.649***
ln(seedrate)	0.416***	0.115*	ln(seedrate)	0.255***	0.155***
IRRIG	0.0946***	0.07	IRRIG	0.0467**	0.0730***
HRV	0.0161	0.0169	HRV	0.0128	0.0482**
IRV	0.0430~	0.0509*	IRV	0.0622***	0.0503***
STK	0.0138	0.0633**	STK	0.0222	0.0552***
NRTH	-0.0151	0.0571***	NRTH	0.0103	0.0374**
WEST	-0.0856**	-0.0221	WEST	-0.0510*	-0.0478***
EAST	-0.0445	-0.144***	EAST	-0.0091	-0.0426
ZJun	-0.0111**	-0.0512***	ZJun	-0.0122***	-0.0174***
ZJun2	-0.0016	-0.0090***	ZJun2	-0.0017**	-0.0020*
ZJul	-0.0612***	-0.0106	ZJul	-0.0319***	-0.0004
ZJul2	-0.0168***	-0.0001	ZJul2	-0.0123***	0.0003
ZAug	-0.0049	-0.0045	ZAug	-0.0041	-0.0137***
ZAug2	-0.0043**	0.0030~	ZAug2	-0.0047***	-0.0001
Constant	-0.993***	0.32	Constant	0.444*	1.285***
			lnsig2v	-4.438***	-4.800***
			lnsig2u	-3.036***	-3.030***
Obs.	1,794	1,901	Obs.	1,794	1,901
R-squared	0.513	0.45	Pseudo L-L	180344.7	256566.2
F-statistic	61.97	58.41	Wald chi2	1035.47	1013.95

*** p<0.01, ** p<0.05, * p<0.1, ~ p<0.15

Table 7. Model 1 average and frontier function joint significance test results.

Average Function Test Statistics			Frontier Function Test Statistics		
	2005	2010		2005	2010
X inputs (F)	223.7700	178.6100	X inputs (F)	790.13	713.6
p > F	0.0000	0.0000	p > F	0.0000	0.0000
Varieties (F)	0.8100	2.7500	Varieties (F)	7.72	12.54
p > F	0.4910	0.0415	p > F	0.0522	0.0057
Regions (F)	1.9700	5.6900	Regions (F)	3.71	19.65
p > F	0.1163	0.0007	p > F	0.2942	0.0002
Z terms (F)	17.4900	9.2000	Z terms (F)	89.32	40.43
p > F	0.0000	0.0000	p > F	0.0000	0.0000
AIC	253.7561	518.2770	AIC	-360,653	-513,096
BIC	341.6314	607.0791	BIC	-360,555	-512,996

Herbicide resistant (HRV), insect resistant (IRV), and stacked (STK) varieties each increase per-acre corn yield by about 5 percent across all regions compared to conventional, non-genetically engineered (NON) seed varieties in 2010. In 2005, only IRV made a significant difference of about 6%. Two explanations are proposed for this difference between years. First, the adoption level of STK was still relatively low in 2005, about 9% compared to about 49% in 2010. As producers learned how to manage the new technology and began to see benefits, the number of adopters as well as the experience in appropriate management practices grew, leading to an increased overall difference in yield between conventional and STK technologies. Second, showing a result contrary to that suggested by previous research, certain transgenic varieties may not be more tolerant to drought than conventional varieties. The presence of drought conditions in 2005 reduced the potential gains of adopting these new seed technologies alone.

Model 2 and Model 3 Estimation Results

To test the impact of variation in drought/moisture conditions on individual seed technologies within regional growing conditions, seed variety dummy variables are interacted with each Z term variable in four variations of Model 2. Model 3 allows for comparison of drought impacts on a single seed variety across regions. It also presents a form of verification for Model 2 results. An interaction between variety, region, and monthly drought index is present in both models. It is expected that the marginal impact of changes in Z on the average yield of a certain seed variety within a selected region—from a Model 3 region-drought interaction—should be similar to the marginal impact of changes in Z on the average yield within the same region for the same seed variety—from a Model 2 variety-drought interaction. For instance, a negative impact estimated from drought interactions with STK in the Model 2 regression for the Heartland is expected to be similar in magnitude to that estimated from interactions with HART in the Model 3 regression for stacked varieties. Estimates for Model 2 are presented in table 8 and estimates from Model 3 are presented in table 9 and additional joint significance tests for Model 2 and Model 3 are presented in table 10.

Inefficiency is again clearly present for all regions and seed varieties, as indicated by the ratio of the error variances. From Model 2, the Northern Crescent resource region has the smallest ratio of inefficiency error variance to random error variance for 2005 and 2010, and the Eastern regions have the largest ratio of inefficiency error variance to random error variance for 2005 and 2010. The larger portion of error due to inefficiency in the Eastern regions may be expected considering the lower importance that corn production has in these regions, which implies less management resources directed toward efficiency in production of corn compared to more locally important agricultural products. From Model 3, conventional seed varieties have the lowest variance ratio for both years, while stacked seed varieties have the highest variance ratio in 2005 but not in 2010.

Table 8. Model 2 frontier estimation results by year and region.

	2005 frontier by region				2010 frontier by region			
ln(yield)	HART	NRTH	WEST	EAST	HART	NRTH	WEST	EAST
ln(yieldgoal)	0.616***	0.894***	0.880***	0.443***	0.547***	0.789***	0.387***	0.929***
ln(seedrate)	0.406***	0.216~	0.0443	0.154***	0.108*	0.244**	0.366***	-0.0847
IRRIG	0.0292	0.0646~	0.0490	0.0107	0.0672*	-0.0798	0.174***	0.202***
HRV	0.0066	0.0984	0.120**	0.0347	0.0599	0.0706	0.334**	0.132
IRV	0.0541**	0.207	0.165***	0.0920	0.0315	0.346**	0.245**	0.151
STK	0.0457~	-0.0570	0.114~	0.0512	0.126***	0.0812	0.0691	0.147
ZJun	-0.0135	0.0279	-0.0269	-0.0435	-0.0512***	-0.0231**	-0.0844~	-0.108***
ZJun2	0.0018	-0.0254***	-0.0052~	0.0051	-0.0074***	0.0012	-0.0079	-0.0394***
ZJul	-0.0238**	-0.0241*	-0.0295	0.0293	0.0277***	-0.0126	-0.0488	0.0993**
ZJul2	-0.0177**	0.0064	0.0305	-0.0073	0.0035***	-0.0009	-0.0232	0.0116*
ZAug	0.0105	-0.0129	-0.0794***	-0.0053	-0.0004	0.0054	0.0118	0.123
ZAug2	0.0006	-0.0084~	-0.0169***	0.0208	0.0080***	-0.0016	-0.0071	-0.0546
HRV_ZJun	0.0029	0.0046	0.0131	0.0619~	0.0578**	-0.0313	0.0431	---
HRV_ZJun2	-0.0015	-0.0057	0.0053	-0.0082	0.0108**	-0.0128	-0.0028	0.0743***
HRV_ZJul	0.0149	-0.0246	0.0139	-0.0698	-0.0277*	-0.0120	0.218	-0.111***
HRV_ZJul2	0.0052	-0.0297~	-0.0442	0.0053	-0.0029~	0.0008	0.0493*	-0.0221***
HRV_ZAug	-0.0309~	-0.0195	0.109***	-0.0010	-0.0245*	-0.0134	-0.0737	-0.0422
HRV_ZAug2	-0.0083*	0.0018	0.0226**	-0.0251	-0.0135**	0.0070	0.0067	0.0285
IRV_ZJun	-0.0053	-0.0001	0.0239	-0.114	0.0271	0.0812**	0.0626	0.113**
IRV_ZJun2	-0.0052	-0.0011	0.0064~	-0.0433	0.0063*	0.0122	0.0044	0.0743**
IRV_ZJul	0.0098	0.0273	0.0178	-0.0911~	-0.0261*	0.0850**	0.176~	-0.144*
IRV_ZJul2	0.0050	-0.0333~	-0.0461	-0.0222~	-0.0032	0.0083*	0.0424**	-0.0234**
IRV_ZAug	-0.0030	-0.0512	0.0814*	-0.0787	-0.0148	-0.0473**	-0.0241	-0.216
IRV_ZAug2	-0.0010	0.0207	0.0148*	-0.0259	-0.0072~	-0.0008	0.0127	0.0885
STK_ZJun	0.0221	0.0269	0.0648	0.0322	0.0457**	0.0414~	0.0885~	0.0650
STK_ZJun2	0.0021	0.0141	0.0102*	-0.0040	0.0056*	0.0073	0.0095	0.0281
STK_ZJul	-0.0632**	-0.0037	-0.0298	-0.0553	-0.0375***	-0.0079	0.0071	-0.0788
STK_ZJul2	-0.0125	-0.0037	0.0061	-0.0134	-0.0043***	-0.0015	0.0204	-0.0055
STK_ZAug	-0.0182	-0.0208	-0.0360	---	-0.0070	-0.0114	0.0182	-0.0993
STK_ZAug2	-0.0142***	0.0085	-0.0120	---	-0.0086**	0.0065	0.0112	0.0452
Constant	0.719**	-0.0479	0.447	2.327***	1.946***	0.190	1.780***	0.593
lnsig2v	-4.985***	-4.264***	-5.274***	-5.388***	-5.273***	-4.890***	-5.494***	-7.041***
lnsig2u	-3.153***	-3.336***	-2.406***	-2.199***	-3.139***	-3.629***	-3.041***	-1.595***
sig2u/sig2v	6.246	2.529	17.60	24.26	8.449	3.529	11.62	231.8
Observations	816	341	440	197	935	312	447	207
Pseudo L-L	230240.9	63395.91	-860.838	-6478.6	227999.1	144284	56189.02	-25082.8
Wald Chi2	534.71	495.17	2296.87	---	508.41	918.85	1838.66	7549.42

*** p<0.01, ** p<0.05, * p<0.1, ~ p<0.15

Table 9. Model 3 frontier estimation results by year and seed variety.

	2005 frontier by seed variety				2010 frontier by seed variety			
ln(yield)	NON	HRV	IRV	STK	NON	HRV	IRV	STK
ln(yieldgoal)	0.783***	0.703***	0.686***	0.574***	0.760***	0.734***	0.470***	0.532***
ln(seedrate)	0.362***	0.349***	0.142	0.301*	0.178~	0.123	0.266***	0.190**
IRRIG	0.0444	0.0622	0.0401	0.0634	0.0630	0.131	0.130**	0.118***
NRTH	0.0163	0.108~	0.188	-0.177***	-0.0429	-0.0037	0.248***	-0.0934
WEST	-0.149**	-0.0477	-0.0585	-0.0851	-0.0643	0.262	0.115	-0.161***
EAST	0.0279	-0.0231	-0.270**	-0.467***	-0.158	0.0573	0.206	0.0294
ZJun	-0.0167~	-0.0120	-0.0174*	0.0224	-0.046***	0.0108	-0.0194	-0.0070
ZJun2	0.0005	0.0005	-0.0033	0.0079	-0.0068**	0.0047	-0.0005	-0.0019
ZJul	-0.031***	-0.0082	-0.0144	-0.0735**	0.0229**	0.0038	-0.0004	-0.0089
ZJul2	-0.0161*	-0.0124	-0.0135	-0.0492	0.0027*	0.0009	0.0002	-0.0006
ZAug	0.0121	-0.0221	0.0056	-0.0101	-0.0051	-0.0317**	-0.0141	-0.0087*
ZAug2	0.0016	-0.0081**	-0.0026	-0.0125***	0.0086**	-0.0062	0.0004	-0.0008
NRTH_ZJun	0.0400*	0.0511~	0.0397	-0.0278	0.0221	-0.0599	0.0858***	0.0384*
NRTH_ZJun2	-0.0238**	-0.0319***	-0.0212	0.0241	0.0080	-0.0157	0.0182**	0.0142**
NRTH_ZJul	0.0033	-0.0347	0.0235	0.0389	-0.0341	-0.0245	0.101***	0.0002
NRTH_ZJul2	0.0218*	-0.0075	-0.0159	0.0323	-0.0037	-0.0006	0.0102***	-0.0002
NRTH_ZAug	-0.0281~	0.0120	-0.0736	-0.0195	0.0077	0.0211	-0.0321**	0.0044
NRTH_ZAug2	-0.0089	-0.0108	0.0167	0.0242***	-0.0102	0.0091	-0.0017	0.0093
WEST_ZJun	-0.0070	0.0019	0.0421~	0.0419	-0.0176	-0.0718	0.0010	0.0141
WEST_ZJun2	-0.0068	-0.0013	0.0060	-0.0008	-0.0015	-0.0188	-0.0022	0.0036
WEST_ZJul	-0.0414	-0.0229	0.0024	-0.0022	-0.0846~	0.252	0.137**	-0.0434
WEST_ZJul2	0.0517~	-0.0025	-0.0058	0.110*	-0.026**	0.0406	0.0209*	-0.0035
WEST_ZAug	-0.109**	0.0173	-0.0645*	-0.120*	0.0224	0.0040	0.0033	0.0254
WEST_ZAug2	-0.0256***	0.0050	-0.0100	-0.0195	-0.0075	0.0182~	0.0062	0.0021
EAST_ZJun	-0.0075	0.0237	-0.0900	0.0816*	-0.130*	-0.109~	-0.0364	-0.0947***
EAST_ZJun2	-0.0013	-0.0040	-0.0161	-0.0227	-0.0537*	0.0312	0.0139	-0.0151
EAST_ZJul	0.0022	-0.0394	-0.0438~	-0.192***	0.0810	-0.0318~	0.0140	0.0711***
EAST_ZJul2	0.0013	0.0086	0.0075	0.432***	0.0083	-0.010***	-0.0039	0.0156*
EAST_ZAug	-0.0117	0.0554	-0.0172	---	0.122	-0.116	-0.129	-0.0342
EAST_ZAug2	0.0024	0.0114	0.0158	---	-0.0371	0.0492	0.0005	-0.0589
Constant	0.0121	0.491	1.319***	1.340**	0.625	1.013**	1.836***	1.860***
lnsig2v	-4.475***	-5.021***	-4.754***	-6.092***	-4.961***	-4.795***	-5.147***	-5.383***
lnsig2u	-3.208***	-2.813***	-2.916***	-3.077***	-3.152***	-2.559***	-3.093***	-3.262***
sig2u/sig2v	3.550	9.098	6.284	20.39	6.10	9.356	7.799	8.339
Observations	686	420	489	199	271	427	351	852
Pseudo L-L	130878	32381.75	57260.01	49004.95	51824.99	740.2219	70228.2	248501.16
Wald Chi2	464.69	710.42	662.28	---	1341.48	65.6	700.03	1543.49

*** p<0.01, ** p<0.05, * p<0.1, ~ p<0.15

Table 10. Model 2 and Model 3 frontier function joint significance test results.

	2005				2010			
Model 2	HART	NRTH	WEST	EAST	HART	NRTH	WEST	EAST
X inputs (F)	261.73	137.28	523.56	51.45	169.31	148.37	718.40	654.99
p > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Varieties (F)	5.52	6.81	9.42	0.73	10.38	7.33	10.07	0.38
p > F	0.1373	0.0782	0.0242	0.8656	0.0156	0.0621	0.0180	0.9440
Z terms (F)	26.90	18.08	33.25	7.47	55.45	20.64	69.09	47.23
p > F	0.0002	0.0060	0.0000	0.2797	0.0000	0.0021	0.0000	0.0000
V x Z terms (F)	30.06	23.91	41.79	10.46	36.39	37.95	80.58	194.61
p > F	0.0369	0.1581	0.0012	0.8416	0.0063	0.0039	0.0000	0.0000

	2005				2010			
Model 3	NON	HRV	IRV	STK	NON	HRV	IRV	STK
X inputs (F)	204.46	156.41	126.77	146.08	154.09	124.51	168.27	437.03
p > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Regions (F)	6.33	4.04	9.69	24.39	1.16	1.78	8.71	10.03
p > F	0.0968	0.2572	0.0214	0.0000	0.7626	0.6202	0.0334	0.0183
Z terms (F)	22.75	31.64	24.94	132.25	33.39	11.55	15.53	8.15
p > F	0.0009	0.0000	0.0004	0.0000	0.0000	0.0727	0.0165	0.2277
R x Z terms (F)	28.99	21.93	34.32	295.91	58.47	27.83	88.05	68.21
p > F	0.0486	0.2352	0.0115	0.0000	0.0000	0.0647	0.0000	0.0000

Yield goal remains significant for all regressions and seed rate is significant in most regressions for both models. Yield goal explains the largest amount of yield variation in all regions and for all seed types. This is as expected since yield goal mostly captures field specific land quality as well as an unobserved history of production practices. Seed rate explains variation in yield as a measure of plant density, assuming higher density brings higher yield with diminishing returns. Yet, yield may also be maximized with lower planting densities in fields where moisture, nutrient or pest conditions are not suitable to support high density planting. Although significant across the full sample in Model 1, irrigation is not an independently significant factor of production within any particular region or seed variety in 2005. Irrigation may have served as a damage control input preventing or reducing yield loss caused by drought stress. Irrigation is significant in several regressions in 2010: IRV and STK seed and HART, WEST and EAST regions responded positively to irrigation use. This may mean that the marginal gain from the availability of water is higher when conditions are not already stressed by lack of moisture, causing significant yield increases instead of preventing yield loss.

Regarding the intercept shifting seed variety variables in Model 2 and region variables in Model 3, adopting GE seed appears to generally improve yield in most regions, while growing in regions other than Heartland tends to result in lower yields for most varieties. The WEST region is the only region to significantly respond positively to adoption of HRV. IRV also increased yield in WEST in 2005 and 2010, while STK caused a potentially significant positive yield response relative to NON in WEST in 2005. GE dummy variables are not significant for any variety in the EAST region for either year or in the Northern Crescent in 2005. The magnitude of significant seed variety variables is much greater in 2010 than in 2005 with the highest effect coming from adoption of IRV in NRTH: using insect resistant seed varieties alone is estimated to increase per acre yield by 35% over conventional seed in the Northern Crescent resource region when moisture conditions are normal, indicated by a Z-index of zero.

Model 3 regional dummy variables measure the relative impact that moving from the Heartland to other resource regions has on average yields for a particular seed variety. Sign and magnitude of these estimates should be interpreted carefully when comparing results to those for Model 2 seed variety dummy variables. For instance, in 2010, Model 3 results indicate that the average yield for STK is estimated to be 16% less when produced in WEST rather than the base region HART without deviations of moisture from normal. A similar result is indicated in Model 2 by the statistically significant 12.6% increase in the average yield in HART when adopting STK rather than NON. The story from Model 2 is that STK performs much better than NON in HART but not much different than NON in WEST in 2010. Worded differently but resulting in the same meaning, from Model 3, STK performs much better in HART than in WEST and NON performs similarly in WEST and in HART.

One result that tells a more easily interpreted story from both Model 2 and Model 3 is adoption of IRV in NRTH in 2010. Model 2 estimates that adopting IRV alone over NON in the Northern Crescent will increase yields 35% assuming zero Z-index values. Model 3 estimates that moving from HART to NRTH when using IRV will increase yields 25%. The difference in magnitude is a result of Model 2 estimating the change to average yields in NRTH while Model 3 estimates change to average yield for IRV. Although magnitudes differ, these results support the conclusion that IRV may be the best option for corn growers in the Northern Crescent.

Marginal Impacts and Yield Predictions

The estimated impact of changes in the drought/moisture conditions as indicated by the significance of Z terms in Model 2 and Model 3 is more specific than in Model 1. The Model 1 estimates are of the aggregate impact of changes in weather across all regions and varieties, while Model 2 and Model 3 estimate weather impacts on regions and varieties separately. For Model 2, the coefficient estimates for the linear and quadratic Z terms without variety interactions are interpreted together as the marginal impact of a one unit change in Z on average yield for the base seed variety in the selected region. This marginal impact in July would be calculated as $\partial \ln yield/\partial ZJuly = \beta_9 + 2\beta_{10}\overline{ZJuly}$ where $\overline{ZJuly}$ is the mean value of the Z-index in July. Adding an alternative seed variety interaction in Model 2 for the same region and month, the impact for IRV for instance would be calculated as $\partial \ln yield/\partial ZJuly = \beta_9 + 2\beta_{10}\overline{ZJuly} + \beta_{21} + 2\beta_{22}\overline{ZJuly}$. Impacts would be calculated similarly for Model 3.

Because the average value of Z is often a negative index number because of above average moisture in many months, resulting in misleading negative values, all marginal impacts are calculated using $Z = 1.00$ for comparison. While the marginal impacts are most adequately estimated at the mean values, inference can still be made about the marginal impacts at higher/lower Z-index values for which the squared coefficient values are important. The marginal impacts are interpreted as the percent change in per-acre yield for a change in Z from 1.00, indicating dry conditions in the normal range, to 1.01, one index unit dryer. Z-term marginal impacts for all months on all seed varieties and regions for 2005 and 2010 are calculated as demonstrated above regardless of statistical significance and presented in table 11.

The most interesting results are found in the Heartland region in 2005 during the month of July. From Model 2, all impacts are negative as expected, but the marginal impact of increased drought on stacked GE seed varieties is more than twice that for conventional seed varieties. This same result is seen when looking at the marginal effect on yield in the Heartland region between STK and NON in Model 3. According coefficient estimates in table 8 and table 9, these marginal impacts are statistically significant. Given this result, the hypothesis that stacked GE seed is more drought tolerant than conventional seed is rejected. Although moisture conditions were much different, with higher moisture on average, the negative impact on STK yield from movement toward dryer conditions in July is also apparent for 2010.

Table 11. Marginal impact on per-acre yield of one unit increase in Z term from Z = 1.00.

Model 2		2005				2010			
		HART	NRTH	WEST	EAST	HART	NRTH	WEST	EAST
Z-June	NON	-0.0099	-0.0229	-0.0373	-0.0333	-0.0660	-0.0207	-0.1002	-0.1868
	HRV	-0.0100	-0.0297	-0.0136	0.0122	0.0134	-0.0776	-0.0627	-0.0382
	IRV	-0.0256	-0.0252	-0.0006	-0.2339	-0.0263	0.0849	-0.0288	0.0748
	STK	0.0164	0.0322	0.0479	-0.0091	-0.0091	0.0353	0.0073	-0.0656
Z-July	NON	-0.0592	-0.0113	0.0315	0.0147	0.0347	-0.0144	-0.0952	0.1225
	HRV	-0.0339	-0.0953	-0.0430	-0.0445	0.0012	-0.0248	0.2214	-0.0327
	IRV	-0.0394	-0.0506	-0.0429	-0.1208	0.0022	0.0872	0.1656	-0.0683
	STK	-0.1474	-0.0224	0.0139	-0.0674	-0.0114	-0.0253	-0.0473	0.0327
Z-August	NON	0.0117	-0.0297	-0.1132	0.0363	0.0156	0.0022	-0.0024	0.0138
	HRV	-0.0358	-0.0456	0.0410	-0.0149	-0.0359	0.0028	-0.0627	0.0286
	IRV	0.0067	-0.0395	-0.0022	-0.0942	-0.0136	-0.0467	-0.0011	-0.0252
	STK	0.0015	-0.0335	-0.1732	0.0363	-0.0086	0.0038	0.0382	0.0049

Model 3		2005				2010			
		NON	HRV	IRV	STK	NON	HRV	IRV	STK
Z-June	HART	-0.0157	-0.0110	-0.0240	0.0382	-0.0596	0.0202	-0.0204	-0.0108
	NRTH	-0.0233	-0.0237	-0.0267	0.0586	-0.0215	-0.0711	0.1018	0.0560
	WEST	-0.0363	-0.0117	0.0301	0.0785	-0.0802	-0.0892	-0.0238	0.0105
	EAST	-0.0258	0.0047	-0.1462	0.0744	-0.2970	-0.0264	-0.029	-0.1357
Z-July	HART	-0.0632	-0.0330	-0.0414	-0.1719	0.0283	0.0056	0.0000	-0.0101
	NRTH	-0.0163	-0.0827	-0.0497	-0.0684	-0.0132	-0.0201	0.1214	-0.0103
	WEST	-0.0012	-0.0609	-0.0506	0.0459	-0.1083	0.3388	0.1788	-0.0605
	EAST	-0.0584	-0.0552	-0.0702	0.5001	0.1259	-0.0462	0.0062	0.0922
Z-August	HART	0.0153	-0.0383	0.0004	-0.0351	0.0121	-0.0441	-0.0133	-0.0103
	NRTH	-0.0306	-0.0479	-0.0398	-0.0062	-0.0006	-0.0048	-0.0488	0.0127
	WEST	-0.1449	-0.0110	-0.0841	-0.1941	0.0195	-0.0037	0.0024	0.0193
	EAST	0.0084	0.0399	0.0148	-0.0351	0.0599	-0.0617	-0.1413	-0.1623

To help visualize these impacts and to account for the jointly significant effects of other factors in the full models, including the relevant upward shifts in production from adopting GE seed generally, per-acre yield predictions were estimated for a range of Z-index values for all regions, seed varieties and years using Model 2 and Model 3 estimates. Yield is predicted using the inverted Z-term—used in regression to aid in uniform interpretation of negative coefficient estimates—but graphed appropriately over the Z-index in its original form, with negative values meaning below normal moisture and positive values meaning above normal moisture. Figures 3 through 6 show predicted yield for every seed variety within every region from Model 2 for 2005 and 2010. Figures 7 through 10 show predicted yield across every region for every seed variety from Model

3 for 2005 and 2010. Because technical inefficiency has been isolated in estimation, these figures represent maximum production frontiers over variation in one month's moisture/drought conditions, using estimated parameters and holding all other production and weather variables constant at their mean values. A vertical band marks the mean Z-index value in the selected month across all seed varieties within each region for Model 2 predictions or across all regions for each seed variety for Model 3 predictions.

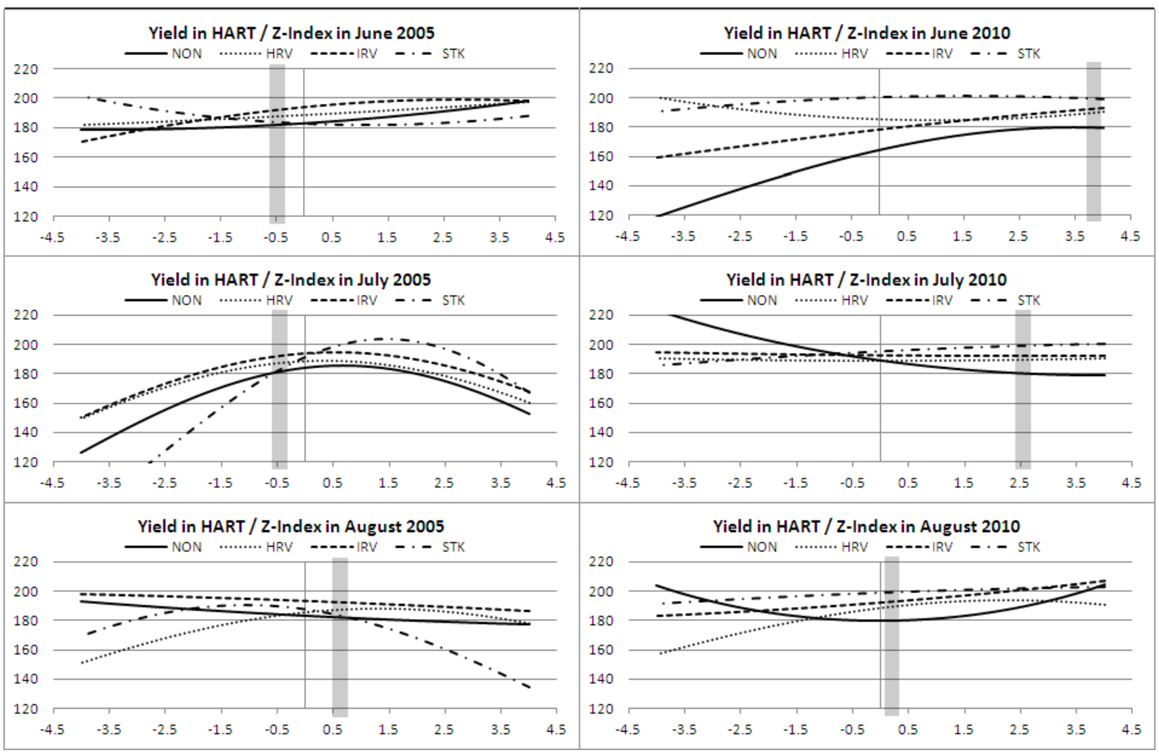

Figure 3. Model 2 predicted per-acre yield for HART region over varying Z-index values (negative Z-index represents drought conditions).

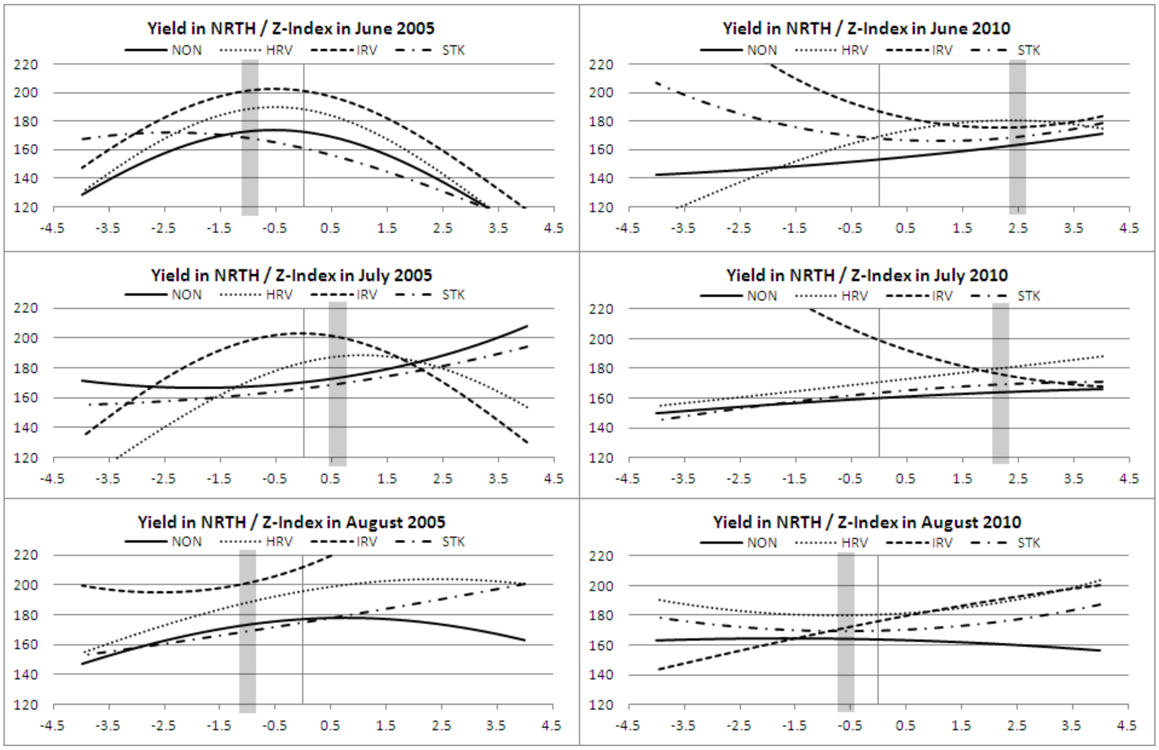

Figure 4. Model 2 predicted per-acre yield for NRTH region over varying Z-index values (negative Z-index represents drought conditions).

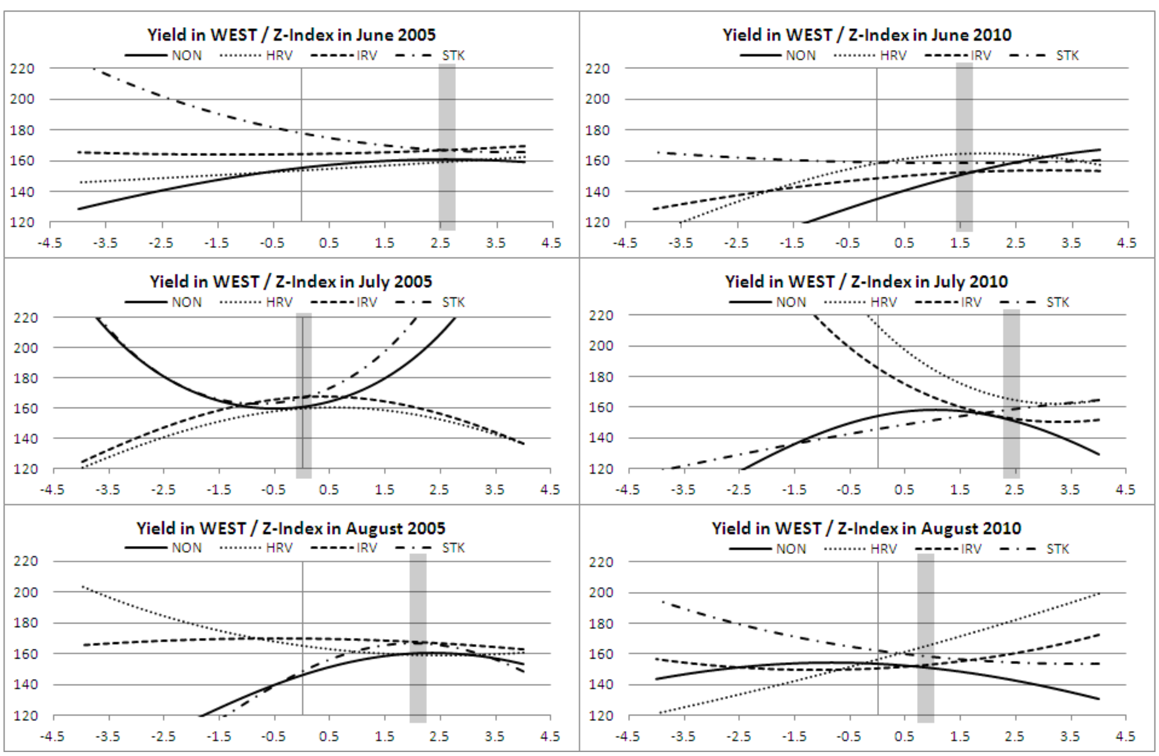

Figure 5. Model 2 predicted per-acre yield for WEST region over varying Z-index values (negative Z-index represents drought conditions).

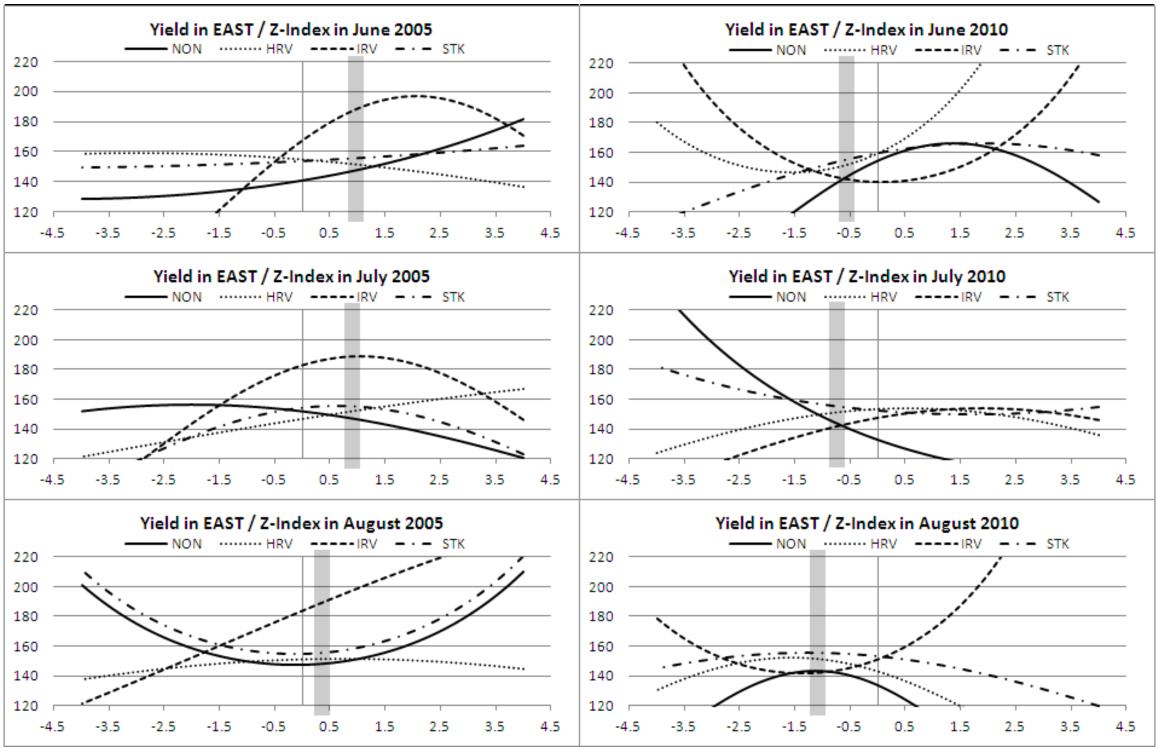

Figure 6. Model 2 predicted per-acre yield for EAST region over varying Z-index values (negative Z-index represents drought conditions).

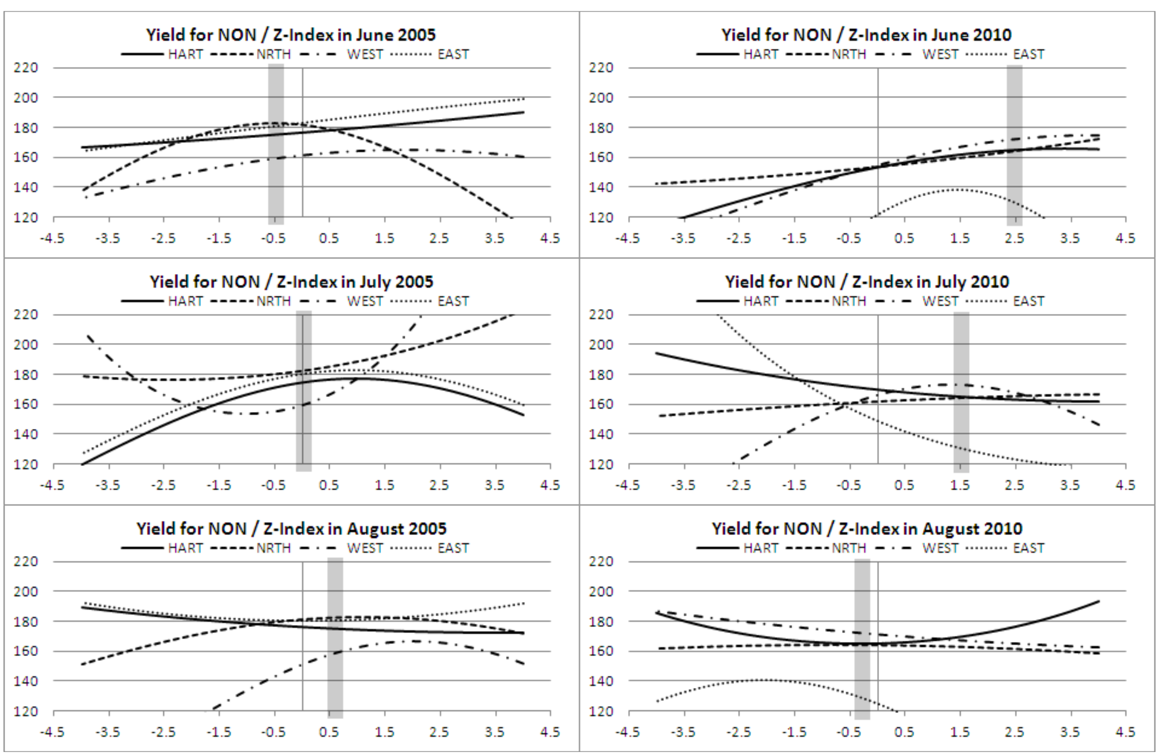

Figure 7. Model 3 predicted per-acre yield for NON seed over varying Z-index values (negative Z-index represents drought conditions).

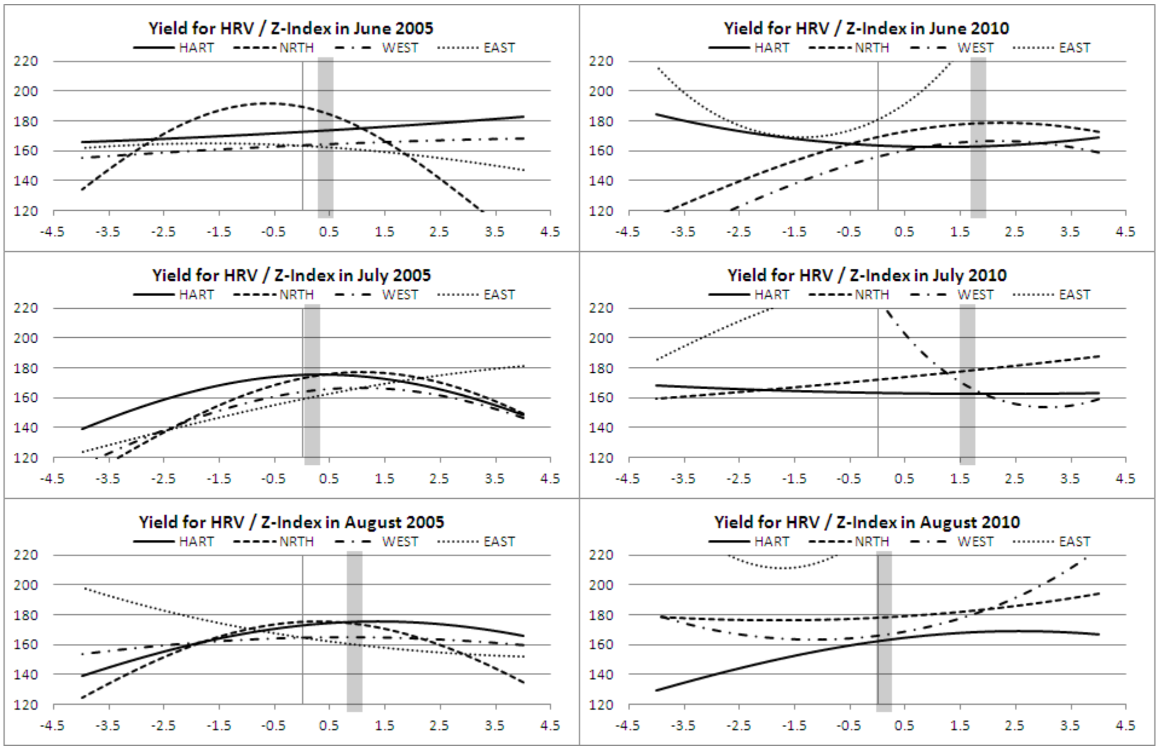

Figure 8. Model 3 predicted per-acre yield for HRV seed over varying Z-index values (negative Z-index represents drought conditions).

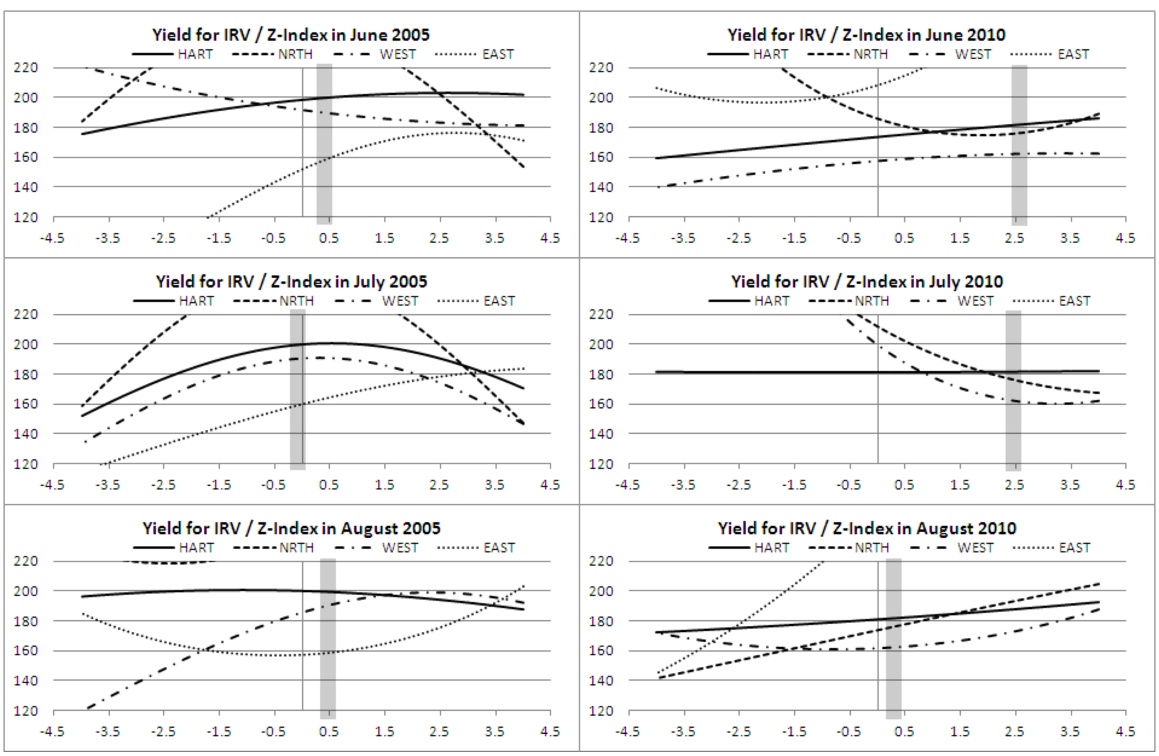

Figure 9. Model 3 predicted per-acre yield for IRV seed over varying Z-index values (negative Z-index represents drought conditions).

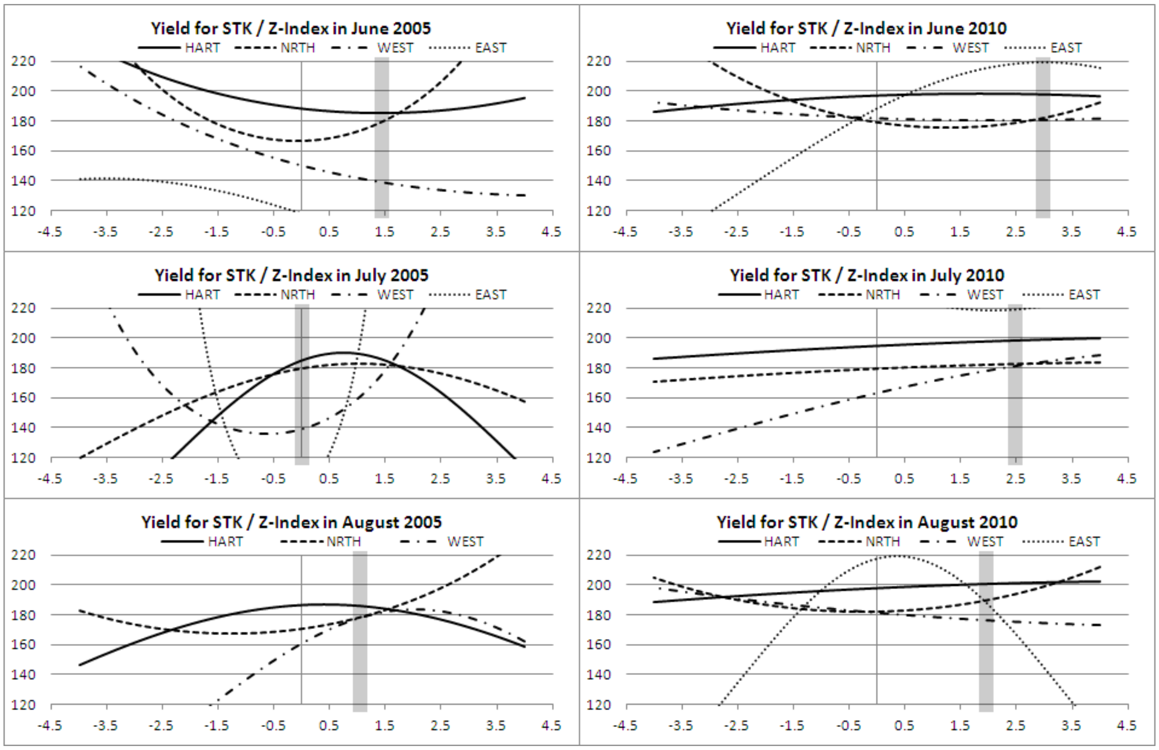

Figure 10. Model 3 predicted per-acre yield for STK seed over varying Z-index values (negative Z-index represent drought conditions).

The sheer number of results makes a complete discussion impractical, but several relevant observations can be easily noted. First, the relationship between yield and moisture levels in July are more economically significant than for June or August. This is the most agronomically critical period of phenological development. Second, the most consistent, believable and interpretable predictions are made for the Heartland and Northern Crescent regions, especially in July. This is true when comparing varieties within regions or comparing regions within varieties. Third, predictions for the EAST region are often erratic, thus strict interpretation should be avoided. This is likely because of the diversity of growing conditions throughout the areas grouped into this category and because of the relatively small number of observations for each seed variety contributing to the estimates. Fourth, moisture conditions within WEST are typically dryer on average than for HART or NRTH. This means optimal conditions may be when the Z-index is larger in positive value—meaning wetter—for WEST than for HART and NRTH.

Fifth, the actual relationship between the Z-index and per-acre yield is likely not simply quadratic across all values. It is believable that there exists an optimal Z-index value for highest yield, with yields decreasing as the Z-index falls from the optimum into wetter or dryer conditions. Yet, the negative marginal impact of increased drought or increased excess moisture would then at some point begin to diminish. Additional increases in drought or moisture would not significantly increase losses. The distribution of yield across all values would resemble a bell shaped curve and a fourth-degree polynomial model would be needed to estimate this relationship. One example from figure 5 can be used to visualize this argument. The curves of all four variety's predicted yields in WEST across the July Z-index for 2005 are inverse of those for 2010. The mean Z-index is near zero in 2005 and around 2.5 in 2010. The curves for HRV and IRV may be approaching an optimum from above in 2010, before the inflection point. The curves for NON and STK may be approaching an optimum from below in 2005, before the inflection point. This pattern is most distinct in this figure, but can be imagined true for others, potentially explaining many convex curves where concave curves were expected.

Technical Efficiency Estimates

Average technical efficiency is predicted for each seed variety and each region in 2005 and 2010 and presented in table 12. Technical efficiency is estimated in several ways. First, total technical efficiency of the entire U.S. corn industry is estimated from Model 1. At just over 82% efficient in 2005 and 2010, the nations corn production appears to be relatively efficient but not increasingly so over the last 5 years. Two efficiency estimates are provided for each year. The first is estimated using the provided representative weights to express the national corn industry's average technical efficiency. The second is estimated using the unweighted sample observations to find the average technical efficiency of the sample only and compare it to the weighted estimate. These values are not significantly different. Using the unweighted sample also allows for additional moments to be expressed.

Table 12. Estimated technical efficiency by year, seed variety, and region.

	2005					2010				
	weighted	sample only				weighted	sample only			
Industry TE	TE	TE	SD	SKEW	KURT	TE	TE	SD	SKEW	KURT
Total	0.8229	0.8224	0.1461	-1.996	7.284	0.8255	0.8168	0.1540	-1.909	7.046
Model 1 TE by Region										
HART	0.8305	0.8328	0.1338	-2.030	7.331	0.8315	0.8255	0.1414	-1.908	7.182
NRTH	0.8245	0.8341	0.1213	-2.037	8.055	0.8377	0.8235	0.1388	-2.276	10.050
WEST	0.8009	0.8092	0.1658	-1.827	6.270	0.8281	0.8257	0.1475	-2.054	8.047
EAST	0.7810	0.7890	0.1777	-1.675	5.583	0.7200	0.7482	0.2157	-1.071	3.212
Model 1 TE by Variety										
NON	0.8242	0.8321	0.1282	-1.821	6.789	0.8177	0.8008	0.1719	-1.628	5.485
HRV	0.8179	0.7994	0.1746	-1.840	6.182	0.7963	0.7945	0.1691	-1.732	6.406
IRV	0.8218	0.8257	0.1365	-2.002	7.095	0.8266	0.8224	0.1506	-1.937	7.006
STK	0.8290	0.8296	0.1565	-2.099	7.159	0.8376	0.8308	0.1393	-2.076	7.951
Model 2 TE										
HART	0.8302	0.8327	0.1424	-1.847	6.427	0.8316	0.8232	0.1481	-1.701	6.253
NRTH	0.8448	0.8522	0.1155	-2.304	9.440	0.8649	0.8523	0.1337	-2.637	12.331
WEST	0.7747	0.7813	0.1808	-1.426	4.738	0.8239	0.8113	0.1624	-1.519	5.460
EAST	0.7544	0.7460	0.1964	-1.142	3.917	0.6990	0.7132	0.2312	-0.719	2.514
Model 3 TE										
NON	0.8330	0.8355	0.1280	-1.857	7.073	0.8341	0.8111	0.1704	-1.675	5.652
HRV	0.8076	0.7855	0.1833	-1.593	5.310	0.7895	0.7790	0.1735	-1.478	5.336
IRV	0.8157	0.8202	0.1464	-1.798	6.204	0.8308	0.8215	0.1586	-1.790	6.332
STK	0.8319	0.8195	0.1803	-1.731	5.482	0.8402	0.8324	0.1486	-1.875	6.903

Estimates under Model 1 by variety and region are taken as averages of selected sub-samples from all estimates from Model 1. These estimates are comparable within the national industry. Model 2 and Model 3 technical efficiencies are from independent estimation of each sub-sample, representing the average technical efficiency within separate, smaller industries categorized by region and variety. The weighted and unweighted estimates are not very different, but the efficiencies are close enough between some regions and varieties that changes in the unweighted sample are enough to change the relative order. From Model 1, weighted TE for HART is slightly greater than weighted TE for NRTH in 2005 and NRTH is greater than HART in 2010, but this order changes when TE is estimated from the unweighted sample. From Model 2, NRTH is more efficient as a region than HART for 2005 and 2010 in both weighted and unweighted estimates, and EAST is the least efficient region in all estimates. Seed variety technical efficiencies are very close within Model 1 weighted estimates in 2005, with STK narrowly edging out NON as the most efficient seed technology. The differences between efficiencies increases in 2010, with STK being two percentage points more efficient than NON. This is due to NON becoming less efficient rather than STK gaining efficiency from 2005 to 2010. From Model 3 estimates, NON edges out STK in 2005 and STK is more efficient than NON in 2010, but both technologies increased average technical efficiency from 2005 to 2010. HRV is the least efficient seed technology in all models in both years.

Standard deviation, skewness and kurtosis statistics represent the spread about the mean, asymmetry of the tail and the "peakedness," respectively, of the frequency distribution of the one-sided technical efficiency estimates. Higher kurtosis describes a sample with a higher frequency of the most frequently observed efficiency which, in this case, is always greater than the mean efficiency; larger negative skewness describes a sample with a higher frequency of "less" efficient producers; and a larger standard deviation describes a sample with a wider variation in efficiency around the mean technical efficiency. From these statistics, it is apparent that the Northern Crescent region has the largest number of the most efficient producers, with observations more tightly concentrated about the mean, but also with the highest proportion of less efficient producers. The same scenario applies to stacked seed varieties in 2010, and also for STK in 2005 but with a higher standard deviation. This is interpreted as meaning STK adopting producers have the highest potential efficiency, with more "winners" over all, but also a greater potential for less efficient producers to be significantly inefficient.

Conclusion

Results from recent studies suggest that U.S. corn production has become more tolerant to drought over time and that this tolerance has come about as a indirect influence of the nationwide adoption of first generation transgenic corn seed technologies (Yu and Babcock 2010, Roberts and Schlenker 2011, Vado and Goodwin 2010). These seed technologies were genetically engineered primarily to provide labor and cost saving alternatives to conventional methods of control of yield reducing damage from weed and insect pests during production. It has been proposed that the high degree of effectiveness of this control has improved the growing environment such that healthier corn plants are able to withstand higher levels of drought stress. To further research into the relative tolerance of transgenic corn seed yields to drought, analysis is needed that isolates the influence of adverse weather on alternative corn seed technologies facing similar conditions. It has been the purpose of this study to compare the influence of drought on per-acre yields for three transgenic corn seed varieties to the impact of drought on conventionally developed seed varieties using field-level production variables in micro-econometric models grounded in economic production theory.

This study directly tests the hypothesis that current, widely adopted transgenic corn seed technologies are more drought tolerant than conventional, non-genetically engineered corn seed varieties. Stochastic frontier analysis is applied to per-acre yield functions for four alternative seed technologies within four U.S. farm resource regions using field-level data from 2005 and 2010 USDA ARMS corn production data. Drought impacts on yield are estimated by incorporating interactions between seed varieties and a monthly drought index for each region and interactions between regions and drought index for each seed variety using three specifications of the stochastic production frontier. Marginal drought impacts, predicted yields and technical efficiencies are estimated for each seed variety and region.

Results indicate that conventional seed varieties and stacked GE seed varieties are nearly equal in technical efficiency when analyzed as separate corn production industries in 2005 and 2010, using the weighted technical efficiency estimates from Model 3 presented in table 12. Stacked varieties are the most efficient in both years when comparing sub-groups of the national industry's estimated technical efficiency from Model 1 in table 12. Varieties with herbicide resistance only or insect resistance only tend to be used on slightly less efficient farms: production of HRV is always the least efficient but production of IRV was more efficient than NON in 2010 according to Model 1 estimates. The change in efficiency of production using NON technology from 83% in 2005 to 80% 2010 within Model 1 could be influenced by changes in adoptions levels. It may be that, as the number of adopters of STK technology increased, the producers transitioning from NON to STK between 2005 and 2010 were the more efficient producers using NON in 2005, leaving a smaller group of less efficient producers using NON in 2010.

In answer to the tested hypothesis that GE corn seed is more drought tolerant than conventional corn seed, the results indicate that estimating these relationships depends upon the region of interest, the presence of drought, and the timing of the drought. Previous studies concentrated analysis on selected counties in major corn growing states within the Corn Belt region of the United States. Focusing on the Heartland region and the important crop development month of July, the current results indicate that, although stacked GE seed varieties may have the highest technical efficiency, the highest potential yields, and the largest potential profits under optimal growing conditions, in the presence of moderate drought conditions, stacked seed has the largest marginal loss in yield such that per-acre yield will fall below that of conventional seed or other GE seed. This is seen clearly in the panel of predicted yield in HART over a range of Z-Index values in the month of July in 2005 presented in figure 3.

Results indicate that, for Heartland corn producers, stacked trait, genetically engineered seed varieties appear to be the best choice to increase potential maximum yield, but they carry the risk of suffering higher yield losses when moisture levels fall below normal conditions. This conclusion of lower drought tolerance for the most widely adopted GE corn seed technology is a rejection of the hypothesis that GE seed are more drought tolerant than conventional seed. The greater potential for higher yields along with the greater potential of lower yields as a result of this relationship is echoed by the distribution of the technical efficiency estimates as mentioned above.

Stacked seed varieties may perform better than conventional under certain conditions in the Northern Crescent resource region, but not as well as HRV or IRV alone. Producers in this region may be best served by selecting specific benefits from individual GE traits. Yields for the WEST region are tightly layered around the mean Z-index value, with STK and IRV performing better than HRV or NON in 2005 at the mean and STK and HRV performing better than IRV and HRV in 2010 at the mean. It is not clear whether any seed variety would perform significantly better as drought falls below normal in the already dryer than desirable Western corn growing areas, but is is possible to visualize stacked seed performing better than conventional seed during wetter than average conditions.

This conclusion supports the recent decision by Monsanto to release their new drought tolerant gene as a stacked trait on top of previously stacked traits for on-farm trials in the Western corn growing region, thereby capturing the potential benefits of GE corn seed technology in both drought and moisture conditions. Adding drought tolerance to stacked GE seed in the Heartland may serve to reduce the larger negative impact of drought on current stacked seed while retaining the higher potential yields obtained under optimum moisture conditions.

This study could be improved in several ways. First, the number of models and interactions could be reduced to simplify and add clarity in interpretation. Considering the erratic and questionable results for the Eastern region, this portion of observations could be omitted. Observations could also be screened geographically to include those within the Heartland region along with only those in the broader but immediately surrounding area to reduce observed heterogeneity. Also, the selected drought variable could be reduced to cover July only and the Z-index results could compared with results using the cumulative Palmer's PDSI (not employed currently due to collinearity between neighboring months). With a smaller geographic region overall, a single model could be estimated similar to a fusion of Model 1 and Model 2 above for the entire sample, with dummy variables for states rather than regions, dummy variables for seed varieties, a single continuous drought index, and interactions between varieties and the drought index. This streamlined model would reduce the total number of interactions and increase the number of drought-variety observations, introducing additional variation across seed varieties.

A second improvement involves testing for the presence of selection bias and omitted variable bias. Efficiency studies can suffer from selection bias when observations self-select into a study sample, violating the random sample assumption (Heckman 1979). The question here is whether the most efficient corn growers self-select into adoption of certain varieties, thus biasing upward the efficiency estimate for those varieties (Crost et al. 2007). The difficulty in correcting such bias in this study involves the number of alternatives to be selected. Rather than choosing between two independent options such as conventional and genetically engineered seed, producers face four alternatives that at times have shared characteristics. A selection correction model for multiple nested alternatives has yet to be developed.

To test for the presence of selection bias, additional models could be estimated that include variables describing producer characteristics that are thought to contribute to inefficiency, such as producer experience and education. These variables are found in the

ARMS Phase 3 cost and returns report rather than the Phase 2 production practices report, which includes a smaller sub-sample of observations at the whole farm level for all agricultural industries rather than the field level for corn only. Reducing sample size will reduce the number of drought observations. Phase 3 was initially decided against in an effort to maximize the variation in the drought index. The same model developed above for Phase 2 could be estimated with Phase 3 to test for robustness of efficiency and drought index estimates. The Phase 3 model could then incorporate additional variables found in the Phase 3 data set to test for omitted variable bias thus the potential for selection bias. These improvements are proposed for later studies since this procedure would provide a more thorough investigation of the efficiency question and possibly provide more robust results of drought impact on alternative seed technologies.

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