Has Technology Increased Yield Risk? Evidence From the Crop Insurance Biotech Endorsement *

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Abstract

The conventional wisdom that technological advances in seed breeding and genetic modification of corn traits has lowered yield risk has recently been challenged by research that argues that the converse is true. The implications of this research have been applied to models of climate change and have led to the conclusion that these technological advances have actually increased agronomic risk, such that climate change is asserted to raise important concerns regarding the stability and viability of corn yields in the future. The argument is based upon assertions that corn yields have become more sensitive to weather stresses. We use corn yields and data from the US federal crop insurance program to evaluate these claims. An examination of yield responses to droughts in 1988 and 2012 suggests more robust yields in the latter period, in spite of very comparable weather stresses. We also use side-by-side data collected under the Biotech Endorsement (BE) between 2008 and 2011. We find that risk, as measured by the rate of indemnities paid per units insured, was significantly lower for crops insured under the BE. We also find that the difference in risk tends to be greater when growing conditions are less favorable.

Key Words: Yield Risk, Biotechnology, Corn Yields

JEL Codes: *Q16, O47, C23*

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Abstract

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Introduction

The US agricultural sector has realized a long and steady pattern of technological advances that have increased corn yields. In recent years, these advances have included improved seed breeding methods as well as genetic modification of corn plant traits. There is no doubt that average corn yields, however or wherever measured, have significantly trended upward over time. Malcolm, Aillery, and Weinberg (2009) measure the recent average annual increase in corn yields to be about 2-3.5% per year. The National Corn Growers Association has asserted that corn yields will reach 300 bushels per acre by 2030—a target that will require substantially greater yield increases in the future.

Recent research has argued that, along with these increases in mean yields, corn has become more sensitive to environmental stresses induced by high temperatures and limited moisture. The literature here is voluminous though much of it is based upon a single data set drawn from historical crop insurance records. This research is almost entirely unanimous in concluding that the risks of crop yields are likely to increase in response to changes in climate variables associated with heat and moisture stresses. A non-exhaustive list of relevant papers include work by D'Agostino and Schlenker (2016), Liu et al. (2016), Roberts et al. (2013), Rosenzweig et al. (2014), Schlenker and Roberts (2009), Tack et al. (2015), Urban et al. (2015), Welch et al. (2010), Lusk, Tack, and Hendricks (2018), and Tack, Coble, and Barnett (2018). Though individual empirical approaches and conclusions differ, most research has found that, although biotechnology has tended to increase average yields, yield risk has increased or, at best, has not been influenced by technological advances. Studies

that have concentrated on the negative effects of increases in warming on corn yield risk include Attavanich and McCarl (2014), Ray et al. (2015), and Urban et al. (2012, 2015).

Perhaps the most prominent research findings suggesting increased corn yield risk are found in a series of papers by David Lobell and his collaborators.[1] The conclusions of this line of research are largely summarized in Lobell et al. (2014). Using these unit-level yield records, Lobell et al. (2014) concluded that technological advances have led to increased planting density of corn and as a result, corn yields have become more sensitive to environmental stresses. Similar research by Schlenker and Roberts (2009) concluded that this increased sensitivity implies that average corn yields in current growing regions is predicted to decrease by 30-46% under the most optimistic climate change scenarios and by 63-82% under the most rapidly warming climate change modeling. Along with an increase in planting density, current technologies have led to a general decrease in chemical and fertilizer inputs. These changes could also contribute to lower yields and increased yield risk in response to climate changes in the future.

It is indeed true that corn planting density has risen significantly over the last 30 years. Figure 1 illustrates state-average planting density (plants per acre) for corn in Iowa between 1963 and 2018. In 1963, Iowa corn growers were planting 13,600 seeds per acre. By 2018, this density had risen to 31,150 seeds per acre. It is certainly true that a denser stand of corn will result in more competition among plants for the available moisture and soil nutrients. Further, insect pressures may increase in more densely planted corn. Based on experimental data collected from 10 site-years of research trials done in Western Iowa, the Iowa State University Extension Service (Wright and Licht (2018)) state that "the recommended plant populations for Iowa are around 34,000-37,000 plants per acre, and these plant populations

[1]Many of these studies use a single data set collected from randomly-sampled, unit-level crop insurance records for Iowa, Illinois, and Indiana. The data are from confidential crop insurance records that span the 1995-2012 period and that have since been made unavailable for follow-up research. An non-exhaustive list includes Roberts et al. (2017), Urban, Sheffield, and Lobell (2015), Seifert, Roberts, and Lobell (2017), and Lobell et al. (2014).

would not need to be changed if row spacing was reduced." Figure 1 includes this recommended density range, which is considerably above the 31,150 average reported by the USDA for 2018. Thus, the evidence does not appear to be consistent with research that asserts a causal relationship between current corn plant densities and increased yield risk.[2]

The research by Schlenker and Roberts (2009) established important nonlinearities and thresholds in corn plant responses to temperature and precipitation. Specifically, they find that corn has a current threshold of 29^o centigrade, beyond which corn yields decrease sharply. The also find important nonlinear yield responses to precipitation, with an optimal level of about 25.0 inches of rain for maximum yields. Tack, Coble, and Barnett (2018) found that climate-driven changes consistent with a 1 C^o increase in temperature would trigger increases in corn yield risk that are expected to increase crop insurance coverage premium rates by 22% relative to current levels. This rate increase rises to 57% with a 2 C^o warming scenario. Tack, Coble, and Barnett (2018) are careful to note that their estimated marginal effects of warming temperatures are conditional on current technology, production, and crop insurance enrollments—factors often neglected in the existing literature.

Tolhurst and Ker (2015) find that the dispersion of yields is increasing and the coefficient of variation of yields is decreasing over time. Li and Ker (2013) find that changes in average yields and the variance of yields due to climate change imply increases in expected crop insurance payouts and actuarially fair premium rates in the Agricorp (Ontario) crop insurance program. Roberts, Schenkler, and Eyer (2012) find that heat, precipitation, and vapor pressure deficits may have important negative influences on corn yields that again imply diminishing yields in response to climate change in the future.

As Li and Ker (2013) note, changes in technology and any resultant increases in the sensitivity of yields to weather have important implications for crop insurance programs. The US federal crop insurance program currently insures in excess of $40 billion in corn liability on

[2]This is not to say that corn yields do not eventually decrease as planting density is increased. Woli et al. (2014) summarize yield data collected from 33 site-years in Iowa from 2006 to 2009 and find that corn yields begin to decrease as seeding density exceeds 38,850 seeds per acre.

over 78 million acres. The subsidized crop insurance program has become the cornerstone of US agricultural programs, accounting for the largest share of spending (excluding nutritional assistance programs) in the 2014 Farm Bill.

The Risk Management Agency (RMA) of the USDA approved a pilot program that offered a significant premium discount on certain types of biotech corn. The program was introduced in 2008 as the Biotech Yield Endorsement (BYE) and was initially restricted to the stacked trait varieties offered by Monsanto in Iowa, Illinois, Indiana, and Minnesota. In 2009, Dupont/Pioneer and Syngenta gained approval for their stacked trait corn hybrids to also be included in the program, which became known as the Biotech Endorsement (BE). The program was extended in 2009 to include Colorado, Kansas, Michigan, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin. The RMA was persuaded that these stacked trait corn hybrids intrinsically had less risk in that they were less sensitive to the very factors that climate change researchers had argued were making corn yields more risky. The pilot endorsement program was eliminated in 2012 under the contention that nearly all corn was of the biotech varieties. The RMA undertook significant rate decreases in important corn growing areas as the BE was terminated under the assertion that biotech corn was less risky and had become ubiquitous in the Corn Belt.[3]

How Do We Measure Yield Risk?

A first fundamental question involves how one measures the risks associated with crop yields. A number of empirical hurdles complicate this seemingly basic question. A simple fact, and one that is indisputable in the empirical literature, is that the technology that is being modeled in this body of research is itself non-stationary and endogenous to variables that include weather as well as government policies and changing market conditions. Nearly all existing research uses yield data collected over time, often over periods as long as 50 years.

[3]For example, in the BE pilot states, the yield protection premium rate for corn on optional units at 65% coverage fell from 6.6% in 2010 to 5.7% in 2012.

Attempts to adequately represent these changes typically include linear or nonlinear trends. More sophisticated approaches include models that allow parametric yield distributions to vary over time (see, for example, Zhu, Ghosh, and Goodwin (2011) and Tolhurst and Ker (2015)). However, any parametric specification of these changes in technology is likely to be fragile and subject to considerable specification biases. This is not to say that existing research has neglected technological change, but rather that the corn of 1990 is simply not comparable to the corn of 2018, much less the corn expected to exist in 2050.

A related concern pertains to exactly how one chooses to represent "risk" in an environment where the second and higher moments of the yield distribution are likely to be simultaneously evolving. It is non-debatable that average yields are increasing. However, arguments based upon a characterization of yield risk using only variance changes are likely to be deficient. Likewise, changes in the coefficient of variation or other related statistics are also likely to have issues with interpretation. In this paper, we argue that one straightforward approach to measuring yield risk is to consider the simple cost of providing a given level of protection against yield shortfalls in an insurance context. Annan and Schlenker (2015) concluded that insured corn and soybeans are significantly more sensitive to extreme heat than uninsured crops and that widespread expansions in insurance coverage of these crops may have important implications for incentives to adapt to climate change. Chen and Chang (2005) and Di Falco, et al. (2014) found that crop insurance may be an instrument useful to stabilize farm revenues under climate changes. The recent papers of Tack, Coble, and Barnett (2018) and Li and Ker (2013) are, to our knowledge, the only existing studies to explicitly consider the costs of crop insurance protection.

The issue of "adaptation" is also a point of contention in how one defines technological change. Lobell (2014) argues that many existing studies confound adaptation to climate changes with many other potential changes in agricultural management and technology that he maintains may improve crop productivity but should not be considered as an adaptation to climate change. Indeed, responses to the aforementioned changes in policies and market

conditions should perhaps not be confounded with changes in technology that represent adaptation. From our perspective, these distinctions may be interesting from an academic perspective but are not likely to be meaningful in addressing the basic issues associated with changes in the technology associated with corn production. We remain agnostic as to how one chooses to characterize changes in yield risk and maintain that such distinctions are largely irrelevant to many of the fundamental issues of interest.

A related point that is often noted in the empirical literature addressing biotechnology and its impacts on yields is that genetic modification is but one of the many changes that have occurred to agronomic technologies over time. It is often noted that significant improvements in seed breeding practices and improved germplasm have had similar or even greater effects on corn yields than have the innovations specific to the genetic modification of corn traits. Other relevant changes might include differences in farmer abilities, education, improved machinery and other capital assets, and changes in the productivity of non-seed inputs. Again, we find these distinctions to be important in framing certain aspects of the yield risk issue, but irrelevant to our basic question of interest—how has the adoption of biotechnology, along with the other concomitant changes in agronomic practices and other inputs, affected yield risk? In our analysis, which is largely based upon empirical comparisons of side-by-side (at least at a county level) production technologies, we are largely uninterested in distinguishing the precise role that genetic modification may play in affecting corn yield risk and rather focus on the central question of whether the adopters of biotechnology have significantly different yield risk than do similarly-situated non-adopters. In a cross-section, it is difficult if not impossible to distinguish adoption of genetically-modified hybrids from other related factors that may be associated with such adoption. This limitation is not unique to our modeling approach. The entire body of literature reviewed above would also have difficulties in separating the impacts of technological change into its individual components. Further, such a decomposition of change into its individual components is not likely to be either relevant or informative in the popular simulations of yield risks 50 years into the future.

From our perspective, one really is not concerned with the question of whether changes are attributable to one factor or another, but rather how the factors collectively will impact yields in the future.

The Biotech Crop Insurance Endorsement

The Biotech Endorsement (BE) was introduced in 2008. The endorsement was the result of a private product submission made by Monsanto to the Risk Management Agency (RMA). The endorsement proposed an actuarially-accurate discount on the yield protection portion of crop insurance premiums that would reflect an asserted reduction in yield risk associated with certain stacked trait corn hybrids. The proposed endorsement was submitted to the RMA in 2007 and subsequently underwent a rigorous review process by RMA staff and by outside expert reviewers. To qualify for the premium discount, growers had to plant at least 75% of the insured acreage in an individual unit to Monsanto branded hybrids (YieldGard VT-Triple and/or YieldGard-Plus). The discount was applied at the unit level and a grower could elect to insure a portion of their overall acreage under the endorsement.

The BE project was motivated by anecdotal observations made by growers and Monsanto sales staff in Illinois in 2005. Illinois experienced a somewhat localized drought in 2005 that ranked among the three worst droughts the state had experienced in over 100 years. The 2005 drought was not as widespread as the 1988 and 2012 droughts and thus did not garner the widespread attention that accompanied the severe droughts in those years. Figure 2 presents Palmer Z Drought Index values across the calendar year for a single National Oceanic and Atmospheric Administration (NOAA) climate division (Division 2, corresponding to Northeast Illinois counties). The figure demonstrates the fact that the growing conditions in this region of the Corn Belt were of a comparable severity to those experienced in the landmark drought years of 1988 and 2012.

In the midst of the 2005 harvest, growers and seed marketing agents observed that the stacked hybrids suffered much less of a yield loss because of the drought. This difference was largely attributed to the healthier and more robust root ball that was provided by the below-ground root-worm protection provided by the stacked hybrids. Figure 3 illustrates a comparison of the root balls for conventional (non-biotech) corn and SmartStax, a Monsanto biotech hybrid. The conventional wisdom advocated by agronomic specialists maintained that the substantial difference in root balls made the biotech corn significantly less sensitive to drought conditions. The argument also suggested that the difference in yields may be negligible in years and areas with sufficient moisture and lower heat stress. However, under conditions of heat and moisture stress, the larger root ball resulted in greater yields and thus less yield stress. The implication for yield risk, however measured, was that the biotech hybrids resulted in significantly less yield risk relative to conventional hybrids (as well as biotech hybrids having only herbicide tolerance).

The analysis of yields, based upon proprietary commercial field trials data, utilized data from 1,637 individual fields (with multiple replications per field) in the initial four-state pilot region comprised of Illinois, Iowa, Indiana, and Minnesota. The data and analysis, which remain confidential, were supplied to the RMA along with actuarial algorithms that measured the relevant rate discounts. The submission contained Figure 4, which illustrated the empirical differences between conventional and biotech corn yield distributions.

The BE was expanded to include stacked hybrids from Syngenta and Dupont/Pioneer in 2009. The pilot area was also expanded to include Colorado, Kansas, Michigan, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin, yielding a 12-state pilot region for the years of 2009-2011. The pilot program was terminated in 2011 and, as noted above, widespread rate adjustments were made to reflect the fact that adoption of the biotech hybrids had increased to the extent that most corn being planted would likely qualify for the BE discount. The BE program resulted in over $532 million in total premium savings, which was derived from a lower premium subsidy ($318 million) as well as lower producer-paid premiums ($214

million). The program was not popular with the insurance companies, adjustors, and agents tasked with administering the endorsement. At the same time that total premiums were being reduced, resulting in less compensation for agents and lower underwriting gains for insurance companies, the companies were tasked with conducting a monitoring program that required genetic testing of sampled leaves to validate that the corn insured under the endorsement was an approved hybrid.[4]

Empirical Analysis

A Comparison of 1988 and 2012 Corn Yields

An initial assessment of the impact of biotechnology on corn yields can be garnered from a consideration of how yields responded during the 1988 and 2012 droughts. In a newspaper article written in the midst of the 2012 drought, Pitt (2012) noted that new corn technology helped to limit corn losses in such a drought. Pitt goes on to quote Secretary of Agriculture Thomas Vilsack, who stated "it is important to point out that improved seed technology and improved efficiencies on the farm have made it a little bit easier for some producers to get through a very, very difficult weather stretch." These statements, which reflect the conventional wisdom of Corn Belt corn growers, are in stark contrast to the assertions of the body of research arguing that biotech corn varieties are likely to be more sensitive to drought. Of course, growers did not have access to genetically-modified corn in 1988, though by 2012, 91% of the corn planted in Iowa was of a genetically-engineered variety.[5]

A first question relates to how the 1988 and 2012 droughts compared to one-another. Figure 5 presents climate variable statistics for every county in the contiguous US. Three

[4]The industry complaint can best be summarized as "more work for less money." An interesting anecdote is that noncompliance was found to be very rare. The limited number of cases that were revealed typically corresponded to growers planting a biotech hybrid that was not on the list of qualifying seed.

[5]Adoption statistics for genetically-engineered corn were collected from unpublished data furnished by the Economic Research Service of the USDA.

weather variables were collected—the May to July averages of the ratios of realized precipitation over normal precipitation, average temperatures over normal temperatures, and the maximum temperatures relative to the normal maximum temperatures. Each of these weather variables has been found to be relevant to corn yield risk in the existing literature. Panels (a), (c), and (e) present the variables for 1988 while panels (b), (d), and (f) present the equivalent statistics for 2012. The figures demonstrate the fact that the weather conditions, at least as measured by these three variables, were similar in 1988 and 2012. Figure 6 presents proportional corn yield changes from 1987 to 1988 and 2011 to 2012. The figure demonstrates that yield losses appear to have been significantly lower in the later period.

Finally, we focus on relative yield changes in the 12 BE states in 1988 and 2012. Panel (a) of Figure 7 presents a plot of yield changes in each county in the two drought years, along with a 45^o line. Observations that fall above the line represent a lower yield decline (or greater yield increase). Although there is considerable variability in the diagram, a majority of the points fall above the line, reflecting less yield loss in 2012. Panel (b) of 7 presents relative yield changes in 1988 and 2012 along with the July Palmer-Z Drought Index, an important indicator of drought stress. The figure illustrates two important points. First, average drought conditions in July in the 12 BE states were worse in 2012 than in 1988. This is evidenced by the mean values of Palmer's Z, which were actually lower in 2012 than in 1988. Second, yield changes in 2012 were less severe in response to the drought than was the case in 1988. Although the average yield changes are similar, most of the 2012 yield changes fall above those observed in 1988. In all, a simple consideration of yield changes between 1987-1988 and 2011-2012 illustrates a more robust response to the drought conditions in the latter period.

The USDA reports adoption of genetically-engineered (GE) corn at the state level. GE corn is summarized by four categories of genetic traits—Bt insect resistance, herbicide tolerance, stacked traits, and an aggregation of all GE hybrids. Of course, none of these GE

varieties were available in 1988. A very simple consideration of the extent to which GE adoption may have been associated with improved yield performance in the presence of severe drought conditions can be revealed by a simple regression of the yield changes on state-level BE adoption. Such a regression is naturally limited by the aggregate nature of the adoption statistics. Table 1 presents the results of regressions of yield changes on aggregate BE adoption. Of course, many other omitted factors would be suspected to have influenced county-level yield changes. However, in every case, a significant positive impact of adoption on yield changes is noted in the regression results.

Evidence From the BE Endorsement

A richer evaluation of the impacts of biotech corn adoption on yield performance can be drawn from county-level data comparing crop insurance performance on those crop insurance units that qualified for the BE to units that did not qualify. Experience data from the BE were obtained via a Freedom of Information Act request from the RMA. The data were supplied at a county-level of aggregation, with the experience data being decomposed into coverage level (50-85%), practice type (irrigated and non-irrigated), insurance plan (revenue and yield protection), and unit structure (optional, basic, and enterprise units). These data were matched to overall crop insurance experience data at the year, county, coverage level, practice, insurance plan, and unit structure and used to derive experience data for the non-BE units. The primary objective is to empirically evaluate crop insurance losses, expressed in terms of the loss-cost ratio (the ratio of indemnity payments to total liability) and the loss-ratio (the ratio of indemnity payments to total premium collected). Two testable hypotheses emerge from this collection of data. First, yield risk, as represented in the loss-cost ratio (LCR), should be lower on those units that were insured under the endorsement and received the premium discount. Second, if the premium rate adjustments were accurate, one would expect the loss-ratios (LRs) to be equivalent across units insured under the endorsement and those not subject to the endorsement discount. In addition, the experience data permit an

evaluation of a central argument inherent in the conventional wisdom regarding biotech corn performance—that the benefits of biotech corn hybrids tend to be greater in areas and years that have less favorable growing conditions.

This comparison is subject to a number of caveats. First, it is likely that a substantial share of the non-qualifying units were also planted to biotech corn hybrids. This may have arisen from limited adoption (i.e., below the 75% acreage requirement) or from biotech hybrids that were not included on the list of qualifying varieties. Likewise, many growers and agents may have simply chosen not to apply for the endorsement because of the additional administrative burden associated with the certification and validation process.[6] The threat of being found in noncompliance, which carried the penalty of being declared ineligible for any indemnity payments, may also have served as a disincentive to participation.

The comparisons are also subject to the limitations associated with the aggregation of experience data to the county level and across different insurance plans and causes of loss. Unobserved heterogeneity within a county may complicate direct comparisons of BE experience to units without the endorsement. Ideally, one would be able to match experience data at the farm/policy level on those policies that had a mix of qualifying and non-qualifying insurance units. However, data confidentiality limitations prohibit such a comparison. The data permit a sort of side-by-side comparison, but only within a county. One may also quibble with the obvious fact that farmers taking the BE endorsement may be intrinsically different from those that declined the coverage. As we have noted, we are less interested in the specific reasons why experience differs but rather with the simple question of whether it differs at all. It could certainly be true that biotech adopters are in some way different from non-adopters (e.g., more efficient, better informed, superior equipment, etc.). However, this is not germane to the fundamental question of whether adoption of biotech corn, along with the concomitant production characteristics of adopters, reduces yield risk.

[6]To qualify, growers had to furnish seed sales receipts that substantiated their claimed plantings.

The analysis is also limited by the fact that most of the experience data are drawn from revenue-protection policies. Such policies cover yield risks but also provide protection against revenue losses triggered by declines in price between planting and harvest. We control for this limitation by including the county-level proportion of indemnity payments made for price declines. Specifically, we collected cause of loss data from unpublished RMA summary of business data and calculated the proportion of indemnities that loss adjustors attributed to a decline in crop price. This limitation is somewhat tempered by the fact that BE and non-BE policies for a given year and county are likely to be subject to identical price declines. Price-based losses may influence the magnitude of indemnity differences, but not the direction.

Table 2 presents summary statistics of the relevant variables. The table demonstrates the differences in LCR and LR and also the difference in premium rates, which averaged 8.94% for the BE units and 10.57% for the non-BE units. Several variables are only observable at the state-level of aggregation. These include crop conditions (Poor Condition), crop progress (Emerged and Silking), and trait adoption (Stacked). The poor crop condition variable represents the percentage of the corn crop that is rated as fair, poor, or very poor at the next to final week of the season. The crop progress variables represent the proportion of corn emerged as of week 20 (mid-May) and silking as of week 30 (late-July). Late emergence and silking may expose corn to greater heat and drought stress during the summer months. We include the average APH yield and the historical average (2000-2007) LCR, both of which reflect general differences in long-term growing conditions and risk in specific counties. We expect the biotech advantage to be greater as APH falls and LCR rises. The proportion of losses attributed to price declines averaged about 6.7%, though this was very year-specific, ranging from 34% in 2008 to less than 3% in other years. In the BE endorsement states, adoption of stacked trait hybrids averaged about 51%. It is notable that only about 26% of the liability and 25% of insured acreage were covered under the endorsement.

The aforementioned caveats associated with this aggregation are applicable here. The experience data were evaluated at two levels of aggregation. The first aggregates all experience data to the year, county, and coverage-level. A finer level of aggregation allows data to be considered at the unit and practice type level. We present results for both levels of aggregation. The finer disaggregation to the unit and practice type can be complicated by the manner in which indemnity data are recorded by adjustors and summarized by the RMA. Due to the occasional occurrence of mixed practices and the assignment of losses to individual units, it is possible to observe negative indemnity payments at the unit/practice level. These anomalies are less common once the data are aggregated across unit and practice types. Data for catastrophic coverage policies were dropped from the analysis.[7]

Our initial evaluation of crop insurance risk differences across BE and non-BE policies included a simple comparison of means and conditional means for the loss-cost ratios (LCR) and loss ratios (LR). Table 3 presents summary statistics for liability-weighted (for the LCR and premium rate) and premium-weighted (for the LR) values of the LCR and LR.[8] Several observations are apparent in the results. First, the LCR is, on average, about 2.7% lower for the BE policies. The endorsement resulted in about a 2% difference in premium rates, with the BE units having a mean rate of about 8.9% and the non-BE units having rates of about 10.6%, suggesting an overall premium discount of about 20% under the endorsement. Average loss ratios tended to be about 23% lower on the BE units, implying that the 2% premium rate difference was conservative and understated the actual difference in risk. The averages are decomposed by coverage level, year, state, practice, unit structure, and insurance plan. In every case, the weighted mean LCRs are lower for the BE units. In the case of loss-ratios, the only case in which BE units realized higher loss ratios occurs for Kansas. The LCR differences are the smallest for 2008, likely reflecting the fact that a significant

[7]Catastrophic, or CAT coverage, is a minimal level of coverage (50% yield and 55% price) that is provided to growers premium-free, save a modest fixed administrative fee. Very few producers take such coverage in the BE pilot area and such policies are not typically representative of overall conditions in these states.

[8]The weighted means are derived from the sum of the numerator variable over the sum of the denominator variable in each ratio.

proportion of indemnities in that year were due to price declines. In 2010 and 2011, the differences were much larger. Participation was greater at higher coverage levels, with the mode of the distribution of participation occurring at 75%. Participation in the BE was the highest in the four original pilot states of Iowa, Illinois, Indiana, and Minnesota, which is not surprising in that an additional year of experience exists for these states. As would be expected, the risk reducing benefits of biotechnology appear to be much smaller for irrigated units, though such units only accounted for about 10% of the participation and were likely to be concentrated in Colorado, Kansas, and Nebraska. The LCR differences are lower for enterprise units, which would be expected in light of the lower overall risk provided by diversification across individual units. The experience is heavily skewed in favor of revenue protection, which is a characteristic of the overall corn crop insurance program.

An alternative consideration of the differences in conditional means can be provided through a comparison of average differences calculated at the individual county-year level. In this case, we can also consider a standard paired t-test of the differences in LCR and LR values. This ignores differences in size and scale across counties. Table 4 presents the average values as well as t-tests of the differences. In nearly every case, the LCR and LR differences are statistically significant. Exceptions include the LCR and LR at the 55% coverage level, the LR in 2008, the LCR and LR for Colorado and Kansas, the LR for Nebraska, and for units insured under the yield protection plan. In every case, these specific categories have relatively little experience, which may make distinguishing the significance of the differences more difficult.

Overall, the results again confirm important differences in the relative risk associated with units insured under the BE endorsement. Premium rates are substantially lower for units on the endorsement, reflecting the premium rate discounts provided under the BE. However, in nearly every case, the loss ratios for the BE policies are significantly lower, suggesting that the discounts may not have been large enough to accurately reflect risk differences.

Richer inferences may be possible with a comparison of the factors associated with the differences in loss cost and loss ratios. That is, a regression of such differences provides a multivariate decomposition of conditional means. A fundamental objective of this analysis is to consider whether the differences in risk, as reflected in insurance indemnity payments, is related to environmental and insurance-related parameters. In particular, we are interested in determining whether factors associated with greater stress or unfavorable growing conditions tend to suggest a larger biotech advantage. To this end, we considered two different sets of regressions applied to the different levels of unit aggregation. Table 5 presents results for the units aggregated to the county, coverage level, and year levels. We present both heteroscedasticity-consistent standard errors and standard errors that allow for clustering within counties. Any observation having no indemnities for both BE and non-BE policies was dropped from the analysis in that such observations provide no relevant information about risk differences.[9] We first consider a simple regression of the LCR and LR differences between BE and non-BE insurance units on an state-aggregate measure of the end-of-season crop condition. We expect states and years with poorer conditions to exhibit a greater biotech advantage. This is confirmed by the regression results. When a greater proportion of the corn crop is rated as being of poor condition, the LCR and LR differences are higher.

We next consider a more detailed regression that includes a variety of environmental and conditioning variables. Table 5 presents regression results and summary statistics for both LCR and LR differences. Indicators of the early progress of the corn crop, as reflected in the percentages of the crop that is emerged in mid-May and that were silking in late-July, have statistically significant effects on the differences in implied risk. The end-of-season crop condition indicator remains statistically significant for the LCR equation, even after conditioning for these two important early season crop progress indicators. A poor crop condition does not significantly affect the LR in the more detailed regression. As would be expected, a greater adoption of biotech hybrids with stacked traits (those hybrids that

[9]This resulted in about 19% of the observations being omitted from this portion of the analysis.

qualified for the endorsement) is associated with a greater biotech advantage, as reflected in lower LCR and LR ratios.

As a greater proportion of indemnity payments that is associated with price declines, the biotech advantage reflected in LCR and LR differences is smaller. Again, this is consistent with expectations in that the technology offers no protection against price-based losses. The regressions include two variables intended to represent the intrinsic quality and risk of growing conditions across the geography of the BE pilot. We include the long-run (2000-2007) historical loss-cost ratio averages and the implied APH yields, which were determined by the accumulated yield histories in each county. In both cases, poorer growing conditions, as reflected in a lower APH yield and a higher historical LCR, increase the risk advantages implied by units insured under the BE endorsement.

Finally, we consider how the advantage differs across coverage levels. In that higher coverage levels tend to have higher risk and thus higher LCR values, one would expect coverage level to increase the difference in LCR. However, the opposite result occurs in the the differences appear to be lower at higher coverage levels. This is also true for the LR regression. This may reflect unobservable differences in growers that tend to purchase higher levels of coverage. Alternatively, this may reflect a significant shift that began in 2008 toward enterprise units at higher coverage levels. This shift occurred in response to policy changes that increased the subsidy on enterprise units. Many growers chose to shift coverage to enterprise units at a higher coverage level. The acreage-weighted average coverage level for corn increased from about 70% in 2008 to 73.6% in 2011 while the acreage enrolled in enterprise units went from 8.2% in 2008 to 45.9% in 2011.

Table 6 present results obtained from an analogous analysis of the experience data at a less aggregated level. In particular, the data are broken down by unit structure and practice type. This finer disaggregation expanded the sample from 8,842 observations to 17,918 while permitting differences in practice and unit type to be distinguished. The results are very similar to those obtained for the more aggregated data. The LCR differences do not appear

to differ for enterprise units or coverage level in this case. Irrigated practice units appear to exhibit a larger difference in the LCR but have no apparent impact on the LR differences. In contrast to the LCR results, the LR differences appear to be greater for enterprise units but smaller at higher coverage levels.

The results largely confirm prior expectations that crop insurance units insured under the BE endorsement realized a lower degree of risk than similarly situated units (in the same county at the same coverage level) that were not insured under the endorsement. The differences in risk are robust across a number of different comparisons and are consistent with a conventional wisdom often expressed during the 2012 drought that technological advances in corn seed and production practices resulted in a lower degree of yield risk.

Concluding Remarks

In all, the results offer several implications relevant to the debate over the impacts of biotechnology on crop yield risk. The implications are, of course, tempered by a number of caveats regarding the nature of the available data. First, anecdotal evidence gleaned from the 1988 and 2012 droughts demonstrates that, although the drought conditions were comparable, the impacts on corn yields were substantially less in the latter period, which was associated with the adoption of biotech corn hybrids. Second, crop insurance risks, as reflected in realized loss cost ratios and loss ratios, appear to be significantly smaller for those units that were insured under the BE endorsement. This difference is consistent across a wide variety of conditioning factors, including year, state, coverage level, unit type, insurance plan, and practice.

It is certainly possible that the differences that are revealed may reflect other unobserved factors that are associated with the adoption of biotech corn hybrids. However, as we have emphatically noted, our results should not be tied specifically to the mere adoption of a particular type of seed but rather to the bundle of seed, environmental, and producer

characteristics that are associated with such adoption. We believe this distinction is likely to be the most relevant to the central question underlying this large body of research—is adoption of biotech corn associated with differences in yield risk? We also confirm that the yield advantages imparted to biotech corn appear to be larger under conditions of greater stress and less desirable production conditions. Poorer conditions of corn at the end of the growing season are associated with greater yield advantages.

We believe that these findings contribute to the growing body of research addressing the relationship between technological advances in agriculture and their relationship to yield risk. We make no assertions as to how crop yields will respond to changes in climatic conditions many years into the future as we believe such assertions are fundamentally flawed by the inability to adequately project what future agronomic technologies will be. Put differently, the confidence intervals associated with such long projections and based upon empirical analyses conducted on yield data from 25-50 years ago are likely to be so wide as to be uninformative. That is not to discredit any such projections, which are certainly of interest to the climate change debate, but rather to limit the implications of our own analysis. Future research has many unexplored dimensions of the issue to explore, including the ex-post specification of technological change, the tenuous linkages between specific climate variables and yield risk, the intra-seasonal timing of yield stresses, and potential issues related to resistance.

Table 1: Regression of 1987/1988 and 2011/2012 Yield Changes on GM Corn Adoption[a]

Parameter	Estimate	Het-Consistent Std. Error	t Ratio	F Statistic	R^2
..... Stacked Trait Adoption					
Intercept	−0.4578	0.0129	−35.39*	49.37*	0.03
Stacked Trait Adoption	0.0026	0.0004	7.08*		
..... Bt Trait Adoption					
Intercept	−0.4710	0.0127	−37.18	83.25*	0.04
Bt Trait Adoption	0.0123	0.0015	8.37*		
..... Herbicide Tolerant Adoption					
Intercept	−0.4701	0.0128	−36.61	73.50*	0.04
Herbicide Tolerant Adoption	0.0084	0.0010	8.57*		
..... All GM Adoption					
Intercept	−0.4671	0.0130	−35.95	64.80*	0.03
All GM Adoption	0.0018	0.0002	7.89*		

[a] An asterisk indicates statistical significance at the $\alpha = 0.05$ or smaller levels.

Table 2: Summary Statistics

	Aggregated Coverage Level		By Unit and Practice	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Coverage Level	0.7403	0.0748	0.7471	0.0681
BE Liability	2,805,761	4,980,505	1,248,938	2,748,301
Non-BE Liability	8,032,964	11,502,464	3,700,757	6,130,394
BE Premium	202,076	337,992	91,179	183,992
Non-BE Premium	732,139	1,016,921	342,360	560,770
BE Acres	4,589	7,489	2,026	4,042
Non-BE Acres	13,999	17,972	6,436	9,610
BE Indemnities	69,016	192,687	33,875	114,217
Non-BE Indemnities	422,312	1,047,585	208,417	601,358
APH Yield	145.06	23.34	147.11	26.45
BE LR	0.4890	1.0872	0.5296	1.2703
Non-BE LR	0.6597	1.1148	0.6940	1.1921
BE LCR	0.0446	0.1078	0.0473	0.1156
Non-BE LCR	0.0744	0.1347	0.0796	0.1436
BE Premium Rate	0.0894	0.0455	0.0920	0.0463
Non-BE Premium Rate	0.1057	0.0513	0.1086	0.0534
Poor Condition	35.8445	12.0742	35.8267	11.8498
Stacked	50.5390	8.4375	51.2335	8.1853
Price-Based Loss	0.0676	0.1591	0.0712	0.1630
Emerged	42.2821	26.9730	42.4277	27.0430
Silking	73.0503	22.4624	73.3773	22.1752
Historical LCR	0.0647	0.0752	0.0592	0.0674
Enterprise	—	—	0.2697	0.4438
Irrigated	—	—	0.0769	0.2664

Table 3: Summary Statistics: Weighted Conditional Means for LCR and LR Differences[a]

Category	N	LCR Difference	LR Difference	Rate Difference
Aggregate Sample				
All	36,969	0.0274	0.2313	0.0191
By Coverage Level				
0.50	942	0.0213	0.1818	0.0224
0.55	182	0.0542	0.4836	0.0138
0.60	757	0.0456	0.1490	0.0472
0.65	5,459	0.0406	0.2425	0.0173
0.70	8,786	0.0560	0.2318	0.0254
0.75	9,700	0.0562	0.2832	0.0227
0.80	7,068	0.0468	0.2114	0.0182
0.85	4,075	0.0443	0.1236	0.0110
By Year				
2008	5,924	0.0134	0.0327	0.0129
2009	11,206	0.0153	0.1046	0.0251
2010	10,666	0.0283	0.2333	0.0232
2011	9,173	0.0233	0.2095	0.0190
By State				
Colorado	159	0.0089	0.0030	0.0259
Illinois	6,864	0.0172	0.1339	0.0163
Indiana	4,505	0.0425	0.3339	0.0230
Iowa	8,050	0.0257	0.2530	0.0142
Kansas	1,216	0.0011	−0.0699	0.0183
Michigan	875	0.0203	0.1760	0.0068
Minnesota	5,138	0.0290	0.2567	0.0198
Missouri	459	0.0328	0.2261	0.0036
Nebraska	4,429	0.0056	0.0227	0.0141
Ohio	1,983	0.0255	0.2419	0.0099
South Dakota	2,137	0.0977	0.6057	0.0360
Wisconsin	1,154	0.0161	0.1162	0.0178
By Practice				
IRR	3,549	0.0060	0.0179	0.0115
NON-IRR	33,420	0.0292	0.2481	0.0198
By Unit Structure				
BU	14,783	0.0246	0.2265	0.0149
EU	9,275	0.0211	0.2062	0.0163
OU	12,911	0.0272	0.1906	0.0181
By Plan				
RP	30,211	0.0284	0.2348	0.0199
YP	6,758	0.0072	0.0753	0.0107

[a] Weighted means calculated as ratios of conditional sums of indemnities, liabilities, and premiums.

Table 4: Summary Statistics: Unweighted Conditional Means for LCR and LR Differences[a]

Category	LCR Difference	t Statistic	LR Difference	t Statistic	Rate Difference	t Statistic
Aggregate Sample						
All	0.0209	29.42*	0.0970	11.79*	0.0144	96.82*
By Coverage Level						
0.50	0.2915	4.47*	0.2915	2.72*	0.0144	11.73*
0.55	0.0934	1.92	0.0934	0.83	0.0144	3.99*
0.60	0.2296	5.26*	0.2296	2.63*	0.0193	10.52*
0.65	0.0867	10.93*	0.0867	3.35*	0.0144	38.21*
0.70	0.0870	13.44*	0.0870	5.26*	0.0154	51.96*
0.75	0.0906	17.04*	0.0906	6.61*	0.0150	53.33*
0.80	0.0941	12.95*	0.0941	6.67*	0.0131	44.83*
0.85	0.0803	8.86*	0.0803	4.20*	0.0124	26.26*
By Year						
2008	0.0091	6.70*	−0.0394	−1.62	0.0104	48.09*
2009	0.0127	11.28*	0.0512	4.00*	0.0160	50.39*
2010	0.0287	18.10*	0.1410	8.17*	0.0162	58.31*
2011	0.0285	19.98*	0.1793	12.54*	0.0130	45.23*
By State						
Colorado	0.0040	0.43	0.0115	0.17	0.0208	9.60*
Illinois	0.0208	14.23*	0.1024	4.35*	0.0147	39.15*
Indiana	0.0273	13.20*	0.1560	8.04*	0.0173	40.24*
Iowa	0.0070	5.86*	−0.0499	−2.38*	0.0117	85.23*
Kansas	0.0042	1.04	−0.0053	−0.15	0.0129*	9.32*
Michigan	0.0313	4.94*	0.1667	2.81*	0.0144	13.76*
Minnesota	0.0149	10.66*	0.1176	6.98*	0.0139	41.08*
Missouri	0.0510	5.28*	0.1782	2.54*	0.0203	11.40*
Nebraska	0.0050	2.93*	0.0032	0.15	0.0111	28.52*
Ohio	0.0334	10.82*	0.2603	10.14*	0.0133	28.36*
South Dakota	0.1043	18.01*	0.5601	15.83*	0.0262	28.84*
Wisconsin	0.0154	4.86*	0.0841	3.52*	0.0147	11.87*
By Practice						
IRR	0.0183	6.13*	0.0827	2.45*	0.0121	34.21*
NON-IRR	0.0212	29.58*	0.0985	11.83*	0.0147	91.35*
By Unit Structure						
BU	0.0212	18.56*	0.0843	5.89*	0.0150	62.96*
EU	0.0225	15.47*	0.1724	11.96*	0.0100	42.48*
OU	0.0195	16.80*	0.0582	4.38*	0.0169	61.11*
By Plan						
RP	0.0235	28.17*	0.1151	14.87*	0.0150	85.20*
YP	0.0114	8.95*	0.0309	1.20	0.0124	47.80*

[a] Average of conditional means at the state, county, and year level. Asterisks indicate statistical significance at the $\alpha = 0.05$ or smaller level.

Table 5: Loss-Cost and Loss Ratio Difference Regressions (Coverage Level/County/Year Aggregation)[a]

Parameter	Estimate	Het-Consistent Std. Error	t Ratio	Clustered Std. Error	t Ratio
Loss Cost Regressions					
Intercept	0.01749	0.00467	3.75**	0.00596	2.94**
Poor Condition	0.00035	0.00013	2.70**	0.00015	2.29**
N		8,956			
F-Statistic		9.83**			
R^2		0.0011			
Intercept	0.06394	0.02282	2.80**	0.02636	2.43**
Emerged	−0.00025	0.00008	−3.14**	0.00009	−2.84**
Silking	0.00030	0.00009	3.27**	0.00011	2.87**
Poor Condition	0.00032	0.00014	2.27**	0.00016	2.04**
Stacked Trait Adoption	0.00145	0.00019	7.59**	0.00027	5.44**
Price-Based Loss	−0.01486	0.00518	−2.87**	0.00602	−2.47**
APH Yield	−0.00064	0.00013	−4.98**	0.00015	−4.38**
Historical LCR	0.20862	0.05482	3.81**	0.06940	3.01**
Coverage Level	−0.06740	0.02457	−2.74**	0.02613	−2.58**
N		8,842			
F-Statistic		67.83**			
R^2		0.0579			
Loss Ratio Regressions					
Intercept	0.06638	0.04153	1.60	0.04650	1.43
Poor Condition	0.00286	0.00121	2.37**	0.00131	2.19**
N		8,956			
F-Statistic		7.53**			
R2		0.0008			
Intercept	0.73615	0.25871	2.85**	0.27502	2.68**
Emerged	−0.00273	0.00079	−3.44**	0.00085	−3.20**
Silking	0.00357	0.00095	3.74**	0.00104	3.42**
Poor Condition	0.00209	0.00133	1.58	0.00142	1.47
Stacked Trait Adoption	0.00782	0.00143	5.47**	0.00177	4.41**
Price-Based Loss	−0.25548	0.06060	−4.22**	0.06445	−3.96**
APH Yield	−0.00259	0.00111	−2.33**	0.00119	−2.17**
Historical LCR	0.79254	0.36394	2.18**	0.41722	1.90*
Coverage Level	−1.13343	0.36248	−3.13**	0.37011	−3.06**
N		8,842			
F-Statistic		22.73**			
$R2$		0.0202			

[a] Single and double asterisks indicate statistical significance at the $\alpha = 0.10$ and $\alpha = 0.05$ or smaller levels, respectively.

Table 6: Loss-Cost and Loss Ratio Difference Regressions (Decomposed by Unit and Practice)[a]

Parameter	Estimate	Het-Consistent Std. Error	t Ratio	Clustered Std. Error	t Ratio
Loss Cost Regressions					
Intercept	0.02307	0.00369	6.26**	0.00607	3.80**
Poor Condition	0.00025	0.00010	2.58**	0.00015	1.71*
N		18,098			
F-Statistic		7.72**			
R^2		0.0004			
Intercept	0.02487	0.01800	1.38	0.02264	1.10
Emerged	−0.00034	0.00007	−5.08**	0.00008	−4.04**
Silking	0.00027	0.00008	3.29**	0.00010	2.55**
Poor Condition	0.00035	0.00011	3.09**	0.00015	2.32**
Stacked Trait Adoption	0.00179	0.00016	10.90**	0.00027	6.58**
Price-Based Loss	−0.01942	0.00415	−4.67**	0.00536	−3.62**
APH Yield	−0.00066	0.00009	−7.23**	0.00012	−5.55**
Historical LCR	0.24915	0.03970	6.28**	0.05790	4.30**
Coverage Level	−0.02794	0.02353	−1.19	0.02745	−1.02
Enterprise Unit	0.00016	0.00267	0.06	0.00298	0.05
Irrigated Practice	0.02981	0.00781	3.82**	0.01020	2.92**
N		17,918			
F-Statistic		67.83**			
R^2		0.0579			
Loss Ratio Regressions					
Intercept	0.08275	0.03609	2.29**	0.04540	1.82*
Poor Condition	0.00224	0.00099	2.27**	0.00118	1.90*
N		18,098			
F-Statistic		6.33**			
R2		0.0003			
Intercept	0.70773	0.22981	3.08**	0.24555	2.88**
Emerged	−0.00370	0.00066	−5.60**	0.00075	−4.91**
Silking	0.00387	0.00074	5.21**	0.00089	4.37**
Poor Condition	0.00168	0.00111	1.52	0.00126	1.34
Stacked Trait Adoption	0.00861	0.00129	6.68**	0.00191	4.51**
Price-Based Loss	−0.27567	0.04583	−6.01**	0.05411	−5.09**
APH Yield	−0.00261	0.00084	−3.09**	0.00097	−2.69**
Historical LCR	0.91126	0.25837	3.53**	0.33549	2.72**
Coverage Level	−1.16056	0.36683	−3.16**	0.37634	−3.08**
Enterprise Unit	0.13829	0.02901	4.77**	0.03302	4.19**
Irrigated Practice	0.09150	0.08092	1.13	0.09702	0.94
N		17,918			
F-Statistic		29.79**			
$R2$		0.0164			

[a] Single and double asterisks indicate statistical significance at the $\alpha = 0.10$ and $\alpha = 0.05$ or smaller levels, respectively.

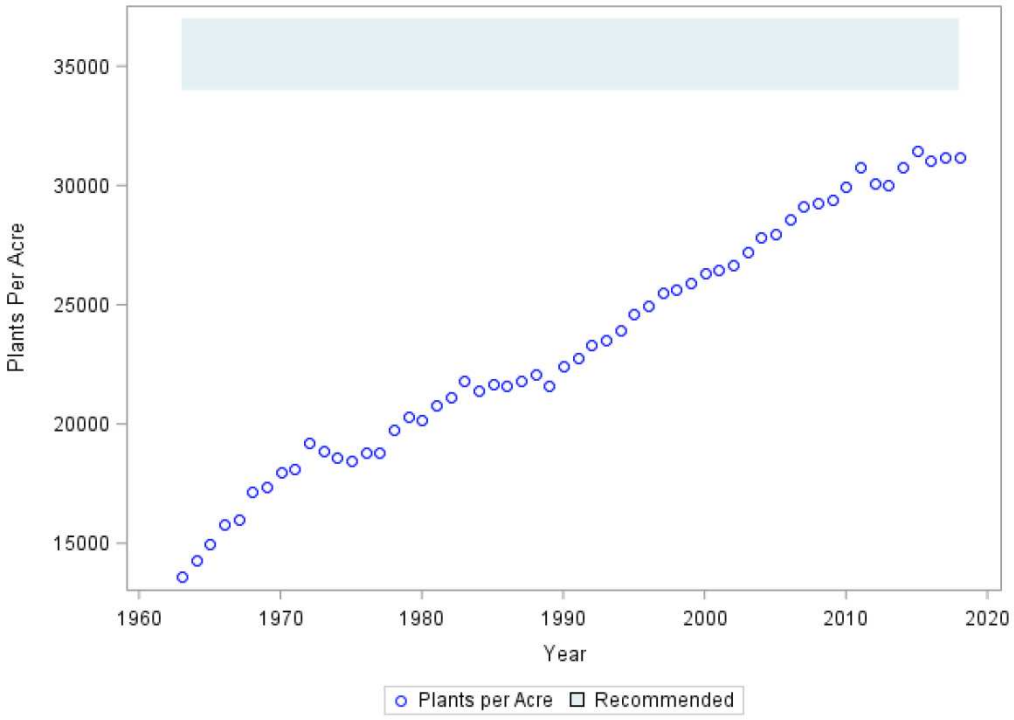


Figure 1: USDA-NASS Average Corn Planting Density in Iowa with ISU Extension Recommended Range

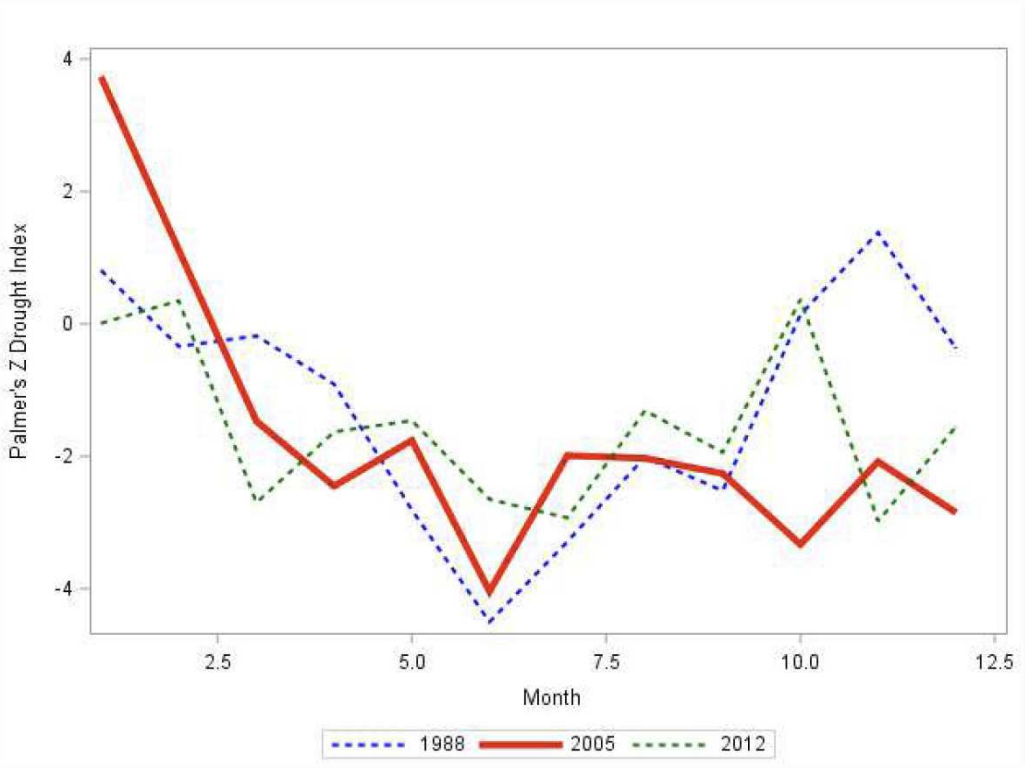


Figure 2: Palmer's Z Drought Index: Northeast Illinois

Figure 3: A Comparison of Corn Root Balls for Conventional Corn (left) and SmartStax Corn (right). (Source: Mycogen Seeds, Agronomy Bulletin 116, "Which Trait Package is Right for You?" August 9, 2015.)

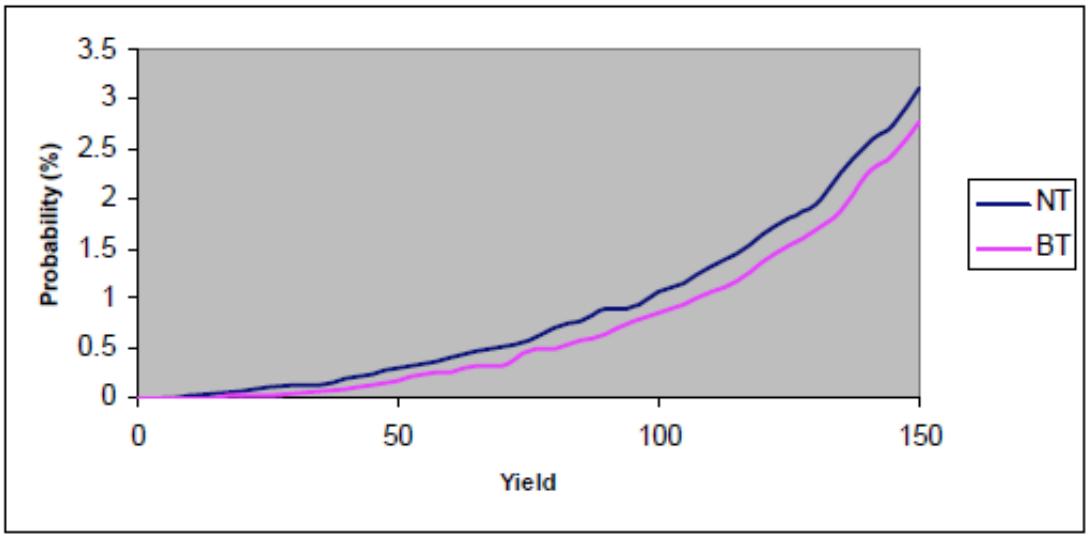
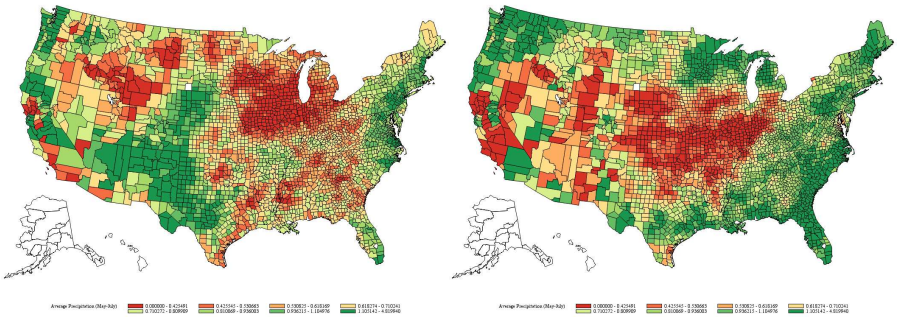
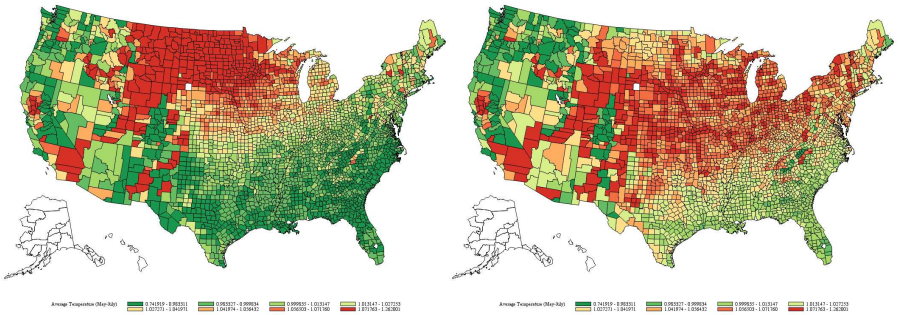


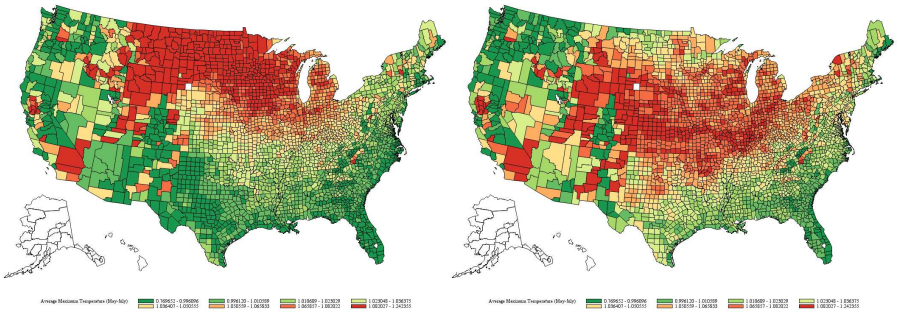
Figure 4: Left-tail Differences in Yield Distributions for Conventional (NT) and Biotech (BT) corn. (Source: Biotech Yield Endorsement Submission and Review Materials.)



(a) 1988 Precipitation (b) 2012 Precipitation

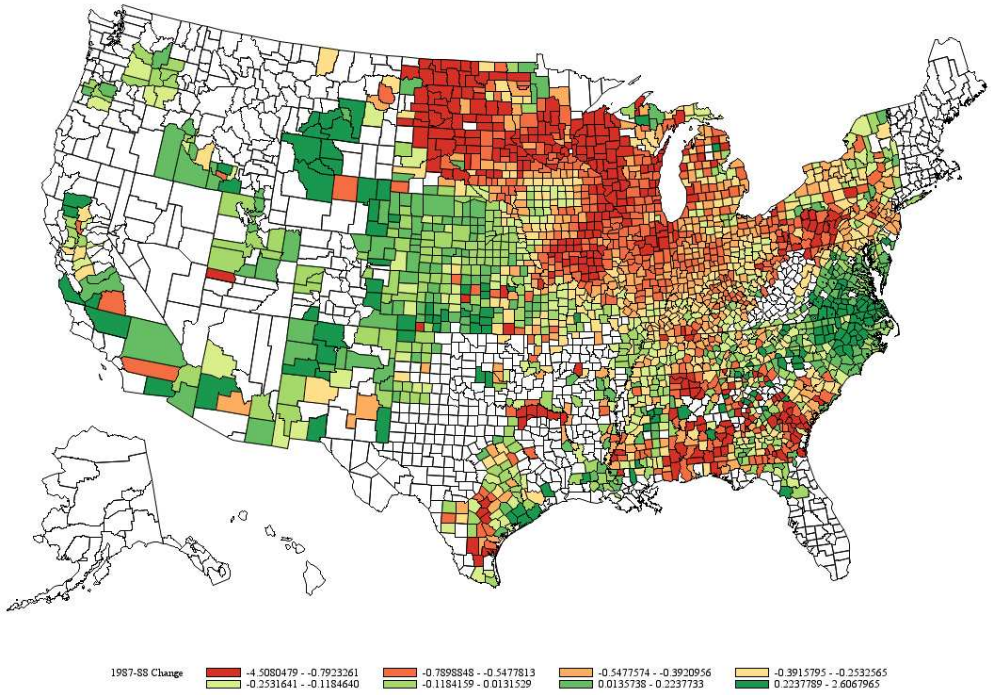


(c) 1988 Temperature (d) 2012 Temperature

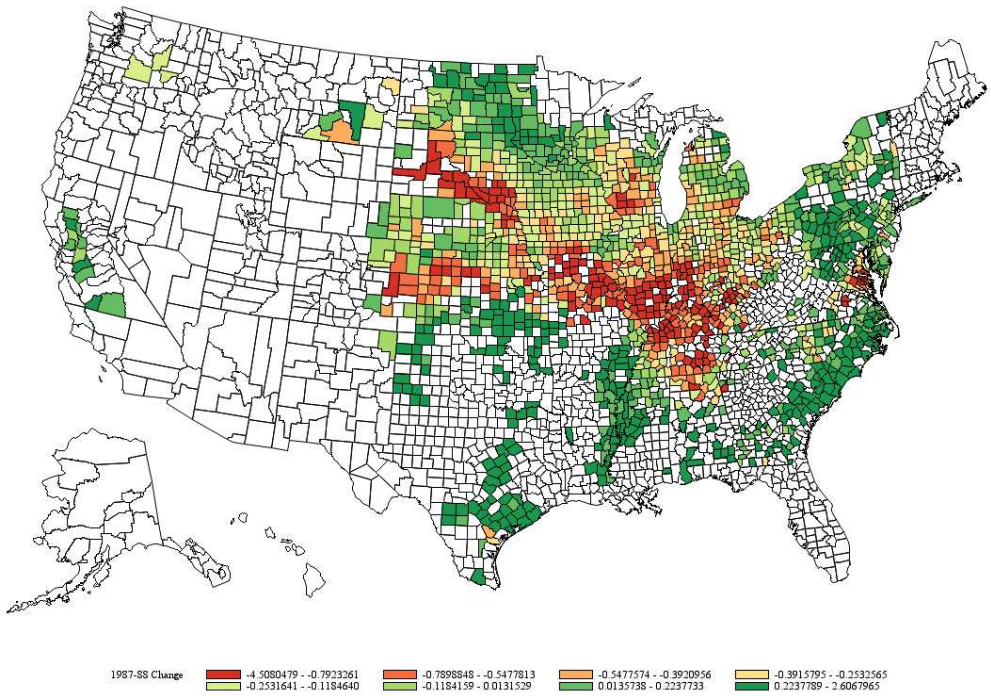


(e) 1988 Max-Temperature (f) 2012 Max-Temperature

Figure 5: Weather Conditions Relative to Normal in 1988 and 2012

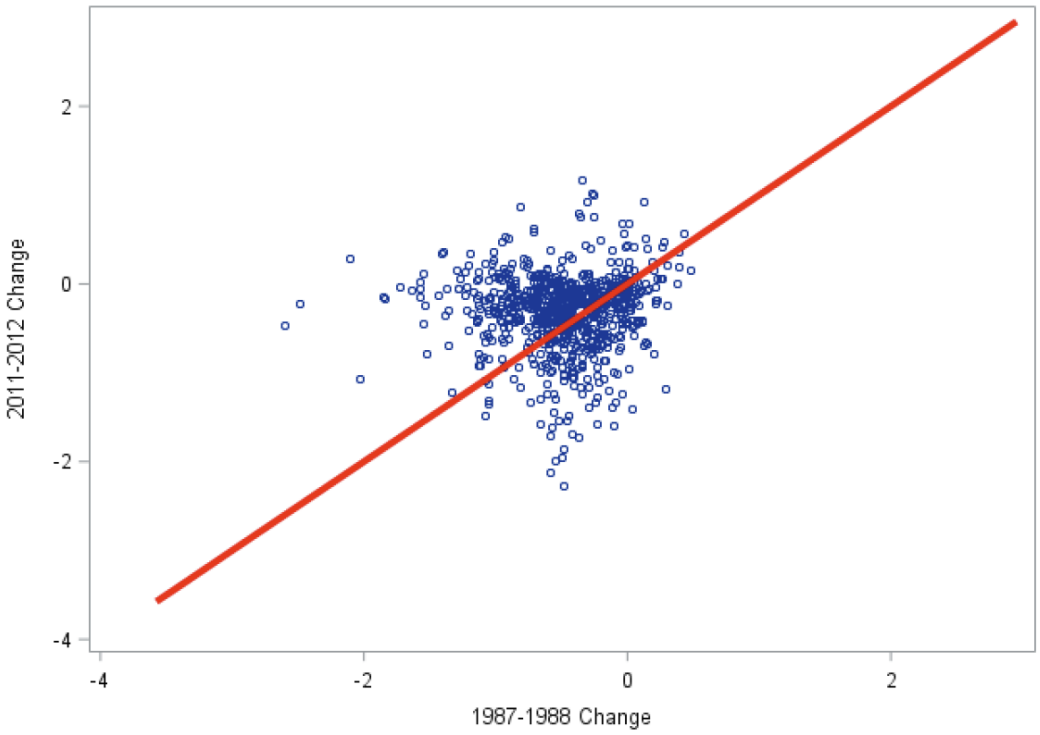


(a) log(1987/1988 Yields)

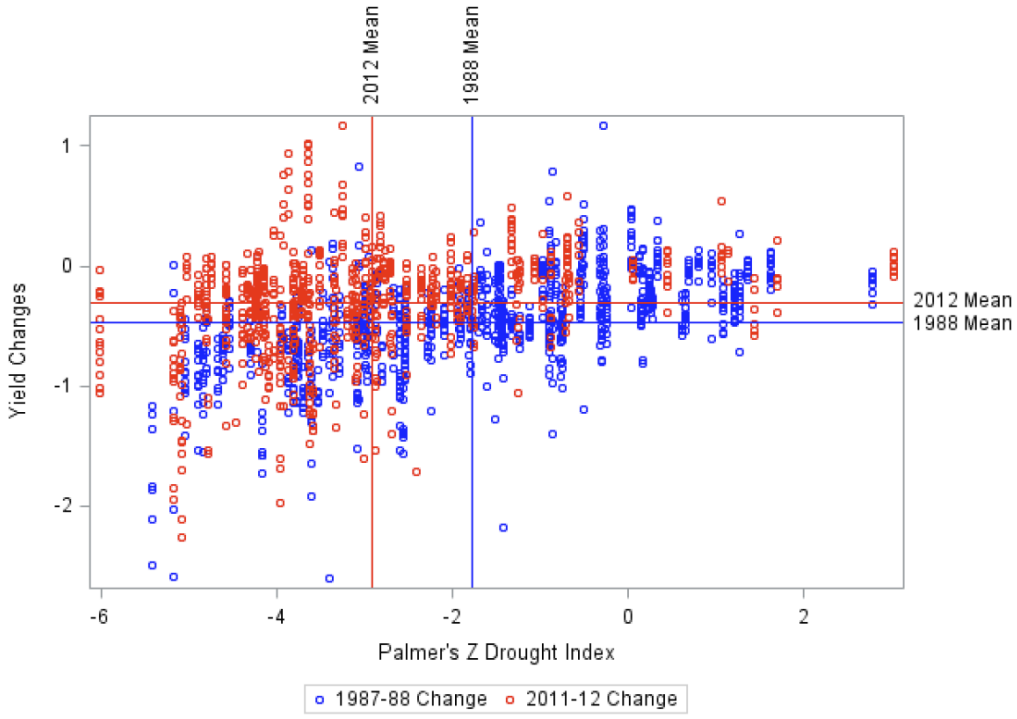


(b) log(2011/2012 Yields)

Figure 6: Proportional Corn Yield Changes



(a) 1987/1988 and 2011/2012 Corn Yield Changes



(b) Yield Changes and the Palmer Z Drought Index

Figure 7: Yield Changes and Drought Conditions in 1988 and 2012

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