Has Technology Increased Agricultural 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 have 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 advances have actually increased agronomic risk, such that climate change is asserted to raise important concerns regarding the stability and viability of agricultural output in the future. In a large body of empirical work, the argument is based upon assertions that corn yields have become more sensitive to weather stresses. This increased sensitivity has coincided with the introduction of a variety of genetically-engineered (GE) crops in the 1990s and 2000s. We use corn yields and data from the US federal crop insurance program to evaluate these claims. An initial 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 next consider side-by-side data collected under the Biotech Endorsement (BE) to the federal crop insurance program between 2008 and 2011. This endorsement provided substantial discounts for growers using certain GE hybrids, reflecting policymakers' beliefs that these hybrids had lower yield risk. 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

Running Head: Has Technology Increased Yield Risk?

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Abstract

The conventional wisdom that technological advances in seed breeding and genetic modification of corn traits have 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 advances have actually increased agronomic risk, such that climate change is asserted to raise important concerns regarding the stability and viability of agricultural output in the future. In a large body of empirical work, the argument is based upon assertions that corn yields have become more sensitive to weather stresses. This increased sensitivity has coincided with the introduction of a variety of genetically-engineered (GE) crops in the 1990s and 2000s. We use corn yields and data from the US federal crop insurance program to evaluate these claims. An initial 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 next consider side-by-side data collected under the Biotech Endorsement (BE) to the federal crop insurance program between 2008 and 2011. This endorsement provided substantial discounts for growers using certain GE hybrids, reflecting policymakers' beliefs that these hybrids had lower yield risk. 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.

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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) estimate 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 and 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 includes work by D'Agostino and Schlenker (2016), Liu et al. (2013), 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 (2017), and Tack, Coble, and Barnett (2018). Though individual empirical approaches and conclusions in the aforementioned literature differ, most research has found that technological advances have increased average yields while, at the same time, making corn more sensitive to the increased heat stress associated with climate change.[1] These empirical results have been used to suggest that climate change threatens the stability and viability of agricultural output and hence food supplies in the future (see, for example, Schlenker and Roberts (2009) and Roberts et al. (2013)).

Perhaps the most prominent research findings suggesting increased corn yield risk are found in a series of papers by David Lobell and his collaborators. Many of these studies use a single data set collected from randomly-sampled, unit-level crop insurance records for Iowa, Illinois, and Indiana.[2] 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 are 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 an average of 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 (2018) states that "the recommended plant populations for Iowa are around 34,000-37,000 plants per acre, and these plant populations 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. The evidence regarding the relationship between planting density and yield risk remains inconclusive, though it is clear that farmers have chosen to increase planting densities over time, as corn yields have risen.[3] Chavas, Shi, and Lauer (2014) also found that a higher density of corn plants contributed to a higher yield.

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. They 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^o centigrade 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^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.[4]

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) simulated the effects of climate change and found that changes in technology and any resultant increases in the sensitivity of yields to weather could imply increases in expected crop insurance payouts and actuarially fair premium rates in the Agricorp (Ontario) crop insurance program. Roberts, Schenkler, and Eyer (2013) 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.

The US federal crop insurance program has become the cornerstone of US agricultural programs, accounting for the largest share of spending (excluding nutritional assistance programs) in the 2018 Farm Bill. The program currently insures in excess of $40 billion in corn liability on over 78 million acres. The Risk Management Agency (RMA) of the USDA, the agency that operates the program, approved a pilot endorsement in 2008 that offered a significant premium discount on certain types of biotech corn. The program, known as the

Biotech Endorsement (BE), was introduced in four states and was subsequently expanded to encompass twelve Corn Belt states. The program was based upon the belief that technological advances in corn production had significantly reduced yield risk. The pilot endorsement program was eliminated in 2012 under the contention that nearly all corn was of the lower-risk biotech varieties and widespread decreases in premium rates were applied in the BE states. These changes signaled a belief on the part of federal policymakers that corn had become less risky as a result of technological change and widespread adoption of biotech hybrids.

We utilize crop insurance experience data collected from policies having the BE and policies from similarly-situated producers (in the same year and county and at the same coverage level) without the endorsement to address the central question of whether adopters of certain stacked-trait, biotech corn hybrids have significantly different yield risk than do non-adopters. We readily acknowledge that adopters may differ in unobserved ways from non-adopters. Our analysis is focused on the central question of how the adoption of biotechnology, taken together with all of the associated differences in producer and farm characteristics, has affected corn yield risk. We compare the loss-cost ratios (the ratios of indemnities to total liability) and loss-ratios (the ratios of indemnities to total premium) across these two different classes of insurance policies. In that the BE was only offered for corn, our results are directly applicable only to corn yield risk. It is possible, if not likely, that biotech adopters and non-adopters are different in other unobservable ways and thus our inferences apply to the entire bundle of grower and farm characteristics that distinguish adopters and non-adopters, at least to the extent that adoption is reflected in participation in the biotech endorsement program. However, this limitation does not diminish the relevance of our results to the central question of whether biotech adopters, along with all of the other concomitant differences that may exist relative to non-adopters, have measurable and meaningful differences in yield risk.

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 that has been established 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. Attempts to adequately represent these changes in technology typically include linear or nonlinear trends.[5] 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. That is, insurance indemnity payments offer a quantitative metric for assessing risk. Existing studies have noted the relationship between crop insurance and climate change. 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 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 linkages between climate, yield risk, and 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 considerations are important but distinct from the basic issues associated with changes in the technology associated with corn production and the implications for the impacts of climate change.

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 but rather is equally applicable to all existing studies that utilize yield data collected over time and across different producers. The entire body of literature reviewed above would also have difficulties in separating the impacts of technological change into its individual components, including behavioral and management changes. Further, such a decomposition of change into its individual components is not likely to be either relevant or informative in the simulations of yield risks 50 years into the future commonly presented in the existing empirical literature. 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.[6]

The Biotech Crop Insurance Endorsement

The federal crop insurance program has existed since 1938 and has become the major policy mechanism for supporting US farmers. The program currently insures nearly \$110 billion in liability and costs taxpayers about \$6.4 billion in premium subsidies and another \$1.5 billion in program delivery costs each year. Premium rates are mandated by statute to be actuarially-fair. Participating farmers receive a premium subsidy that averages about 65%. Private insurance providers are also paid a significant subsidy to administer the program and are granted favorable reinsurance terms underwritten by the treasury. In total, the program costs US taxpayers about \$8 billion per year.[7]

Legislative requirements for insurance premium rates to be actuarially fair have led to a number of changes in the terms of coverage, including endorsements to adjust rates to accurately reflect risk. One such program was introduced in 2008 as the Biotech Yield Endorsement (BYE). The program 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 endorsement was the result of a private product submission made by Monsanto to the Risk Management Agency (RMA). 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 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 crop insurance unit to certain Monsanto-branded biotech 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 seed 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 resulted from the below-ground root-worm protection provided by the biotech 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).[8]

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 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.[9] 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.[10]

Empirical Analysis

An anecdotal 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. This analysis is not intended to provide a definitive conclusion regarding the response of yields to drought, but rather represents a simple comparison of two entirely different technologies (conventional and GE corn hybrids) under comparable heat and moisture stress. Although many other factors relevant to crop yields changed over this period, a fundamental change in technology included the introduction of genetically-modified corn hybrids. 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 and policymakers, are in contrast to the assertions of the body of research arguing that biotech corn varieties and related changes in technology have made corn 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, though only 61% were stacked trait hybrids (USDA-ERS (2019)).

A first question relates to how the 1988 and 2012 droughts compared to one-another. We evaluated monthly (May through July) precipitation totals, average temperatures, and maximum temperatures for both 1988 and 2012. A comparison of weather in 1988 and 2012 to normal weather conditions in each county demonstrated the fact that the weather conditions, at least as measured by these three variables, were similar in 1988 and 2012. That is, the 1988 and 2012 droughts were of a similar severity. We also compared proportional corn yield changes from 1987 to 1988 and 2011 to 2012 and found that yield losses appear to have been significantly lower in the later period.[11]

We next considered proportional yield changes in the 12 BE states from 1987 to 1988 and 2011 to 2012. Panel (a) of Figure 4 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 Figure 4 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 lower in 2012 than in 1988. Second, although the average yield changes were similar, most of the 2011-2012 yield changes were less severe in response to the drought than was the case in 1987-1988.

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

GE corn adoption. Such a regression is naturally limited by the aggregate nature of the adoption statistics.

A simple linear regression model that reveals the impacts of GE adoption can be expressed as

$$y_{it} = \alpha_0 + \alpha_i + \beta_1 * GE_{it} + \beta_2 t + e_{it}, \tag{1}$$

where y_{it} is the logarithmic yield in county i in year t, α_i is a fixed, county effect, GE_{it} is the proportion of acres planted to GE, and t is a linear time-trend. We consider yield changes relative to the previous year, which implies

$$y_{it} - y_{it-1} = \beta_2 + \beta_1 * (GE_{it} - GE_{it-1}) + e_{it} - e_{it-1}. \tag{2}$$

The new intercept β_2 represents the impact of the drought in year t relative to the previous year (1987 and 2011) and β_1 represents the impact of changes in adoption of GE corn, which is fixed at zero in the earlier period. This specification constrains the average proportional differences in yields to be the same for the 1987-1988 and 2011-2012 periods. An alternative version of this specification adds an indicator variable for the latter 2011-2012 period to relax this restriction.[12]

Table 1 presents the results of regressions of yield changes on aggregate GE corn 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. As expected, the intercept terms are all negative, reflecting the proportional decrease in yields as a result of the droughts. The largest GE impact occurs for stacked traits, which is consistent with expectations that the combinations of multiple traits tend to provide the greatest degree of yield protection. When the 2012 fixed effect is added, the results are largely unchanged, though the stacked trait impact becomes negative.

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).[13] These data were matched to publicly-available overall crop insurance experience data and used to derive experience data for the non-BE units.[14] 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). We aggregated the data to a given coverage level, county, and year.[15] 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.

The essential question is whether loss-cost ratios and loss-ratios are significantly different for conventional and GE corn. One aspect of the BE endorsement merits additional discussion. Crop insurance guarantees are based upon an actual production history (APH) yield, which is given by the historical average yield for each unit. The extent of BE adoption that may have been embedded in these historical APH yields is unobservable. Thus, RMA did not adjust APH yields on BE policies to reflect the impact of adoption of GE hybrids. It is possible that an increase in the mean of yields caused by GE adoption could lower indemnities (and thus loss-cost and loss-ratios), even if the variance of yields is unchanged. This goes to the heart of our previous discussion of the appropriate measurement of risk. A constant variance with an increasing mean would lower the coefficient of variation of yields. From the perspective of a farmer or an insurer, this would represent a decrease in risk. We examined the APH histories of yields to consider the extent to which farms with the BE endorsement had higher historical yields, potentially reflecting earlier GE hybrid adoption. The acreage-weighted average APH on BE units was 164.3 bushels per acre while the analogous APH yield on non-BE units was 145.4 bushels per acre. This suggests that APH yields on the BE policies may have had some extent of the biotechnology advantages already embedded in the yield histories. Likewise, these differences may also reflect other unobservable factors associated with the BE policy holders.

We consider differences in means for loss-costs and loss-ratios across a wide range of conditioning factors. We also consider a multivariate conditional mean through the application of a regression model. Define y_{ijt}^{BE} and y_{ijt}^{NBE} to be the observed values of the loss-cost ($j = 1$) and loss-ratio ($j = 2$) variables in county i and year t for BE and non-BE corn. Regression models having two-way, fixed effects variables (county and year) for each value of y_{ijt} can be expressed as

$$\begin{aligned} y_{ijt}^{BE} &= \alpha_{ij} + \alpha_{jt} + \beta_{0j}^{BE} + \beta_{j}^{BE} X_{it} + \epsilon_{ijt}^{BE} && (3) \\ y_{ijt}^{NBE} &= \alpha_{ij} + \alpha_{jt} + \beta_{0j}^{NBE} + \beta_{j}^{NBE} X_{it} + \epsilon_{ijt}^{NBE}, && (4) \end{aligned}$$

where X_{it} is a vector of relevant covariates, α_{ij} and α_{tj} are county and year fixed effects, β_j is a vector of coefficients, and ϵ_{ijt} is a mean zero random error term. We can express these equations in differenced form as follows:

$$y_{ijt}^{BE} - y_{ijt}^{NBE} = (\alpha_{ij} - \alpha_{ij}) + (\alpha_{jt} - \alpha_{jt}) + (\beta_{0j}^{BE} - \beta_{0j}^{NBE}) + (\beta_{j}^{BE} - \beta_{j}^{NBE}) X_{it} + (\epsilon_{ijt}^{BE} - \epsilon_{ijt}^{NBE}), \quad (5)$$

or, in equivalent terms and expressed as an estimable equation as:[16]

$$y_{ijt}^{BE} - y_{ijt}^{NBE} = \gamma_{0j} + \gamma_{1j} X_{it} + \varepsilon_{ijt}. \tag{6}$$

Table 2 presents definitions and summary statistics of the relevant variables. The table demonstrates the differences in LCR and LR and also the difference in premium rates. The LCR is, on average, about 2.82 percentage points lower for the BE policies. The endorsement resulted in about a 1.62 percentage point 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 10.5%. This suggests an overall premium discount of about 19% under the endorsement. Average loss-ratios tended to be about 16 percentage points lower on the BE units, implying that the 19% premium rate difference was conservative and understated the actual difference in risk. If the discount accurately reflected risk differences, indemnities and premiums should have had equivalent adjustments, such that the ratio is unchanged. The loss-cost and loss-ratios are broken out by year and state in Figure 5. Considerable variation in these empirical measures of insurance payments is notable across both states and years. 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 and may also reflect difficulties during planting due to unfavorable conditions. We include the historical average insurance (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 the historical average yield falls and the LCR rises. It is notable that only about 26% of the liability and 25% of insured acreage were covered under the endorsement. Data for catastrophic coverage policies were dropped from the analysis.[17] In the BE endorsement states, adoption of stacked trait hybrids averaged about 51%. With the possible exception of crop conditions, which may be jointly determined with crop insurance outcomes, all of the explanatory factors are exogenous or predetermined relative to the county-level loss-cost and loss-ratios.[18]

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.[19] Several observations are apparent in the results. First, the LCR is, on average, about 2.74% lower for the BE policies. The endorsement resulted in about a 1.92% difference in premium rates, with the BE units having a mean rate of about 7.2% and the non-BE units having rates of about 9.1%, 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 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.[20] 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 LR at the 55% coverage level, the LR in 2008, the LR for Kansas and Nebraska, the LR for irrigated production, the LCR and LR for Colorado, and the LR 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 through 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. 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.[21] A fundamental objective of this analysis is to consider whether the differences in risk, as reflected in insurance indemnity payments, are 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.

It should be noted 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 futures prices observed at the Chicago Board of Trade (CBOT) between planting and harvest. We control for this limitation by including the county-level proportion of indemnity payments made for price declines.[22] This limitation is tempered by the fact that BE and non-BE policies for a given year and county are subject to identical price declines and thus the differences would be transparent to purely price-based losses. 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.

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 NOAA weather divisions. 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.[23]

Indicators of the early progress of the corn crop, as reflected in the percentages of the crop that were 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, even after conditioning for these two important early season crop progress indicators. As would be expected, a greater adoption of biotech hybrids with stacked traits (those hybrids that qualified for the endorsement) is associated with a greater biotech advantage, as reflected in lower LCR and LR ratios.

As the proportion of indemnity payments that is associated with price declines increases, 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 might expect coverage level to increase the difference in LCR. However, it is also possible that indemnities at lower coverage levels represent deeper losses, wherein the biotech advantage is more prominent. Consistent with the latter case, the differences appear to be lower at higher coverage levels. This is also true for the LR regression. This may also reflect unobservable differences in growers that tend to purchase different levels of coverage. Alternatively, this may reflect a significant shift that began in 2008 toward more highly aggregated "enterprise units" at higher coverage levels. This shift occurred in response to policy changes that increased the subsidy on more highly aggregated (enterprise) insurance units.[24]

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.

Our analysis is subject to a number of caveats. First, it is possible that a 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.[25] To the extent this caveat applies, the risk reduction implied by the biotech units will be understated.

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, thereby resulting in a true identical twins comparison. However, data confidentiality limitations prohibit such a comparison. The data permit a sort of side-by-side comparison of yield differences that is robust to unobserved heterogeneity within counties. It is also possible that farmers taking the BE endorsement or those insurance units which are insured under the BE may be intrinsically different from those that do not have the endorsement (e.g., more efficient, better informed, superior equipment, etc.). This remains an important caveat of our analysis.[26] As we have noted, we are less interested in the specific reasons why experience differs but rather focus on the simple question of whether it differs at all.

Concluding Remarks

In all, the results offer several implications relevant to the debate over the impacts of climate change and biotechnology on corn yield risk. It is important to acknowledge that our analysis and conclusions directly pertain only to corn in 12 Corn Belt states. Other crops have also realized significant changes in agronomic technologies, including genetic modification. We urge care in extending our results to other crops or areas.

The implications of our results 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. Finally, because insurance guarantees were not increased under the BE, decreases in loss-costs and loss-ratios may reflect increases in average yields by participants in the program. Although this may be viewed as a decrease in risk by farmers and insurers, it may only reflect changes in the first moment of the yield distribution. Significant differences in existing guarantees between BE participants and non-participants and increases in the loss-cost and loss-ratio differences over time temper this concern.

It is certainly likely that the differences revealed in our analysis, as well as those presented in a voluminous literature reaching directly opposite conclusions, 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, along with all the other concomitant changes, 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. Thus, if climate change worsens growing conditions, the advantages of GE corn would be expected to be more significant relative to conventional corn.

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. This said, we believe that our empirical results, which are consistent with the conventional wisdom typically observed in the agricultural community, stand in stark contrast to the large body of research that has asserted that technological advances have increased risk. Our results demonstrate that biotech corn is *more* resistant to heat and moisture stresses and that this biotech advantage tends to increase as such stresses rise. We certainly do not dispute universal concerns over a changing climate but rather provide evidence that technology may endogenously adjust to be more resilient in the face of such change, thereby alleviating threats to the viability and stability of world food supplies. 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.

Notes

[1]An important exception to these conclusions exists in a recent paper by Chavas, Shi, and Lauer (2014), who found that the negative yield impacts of corn planted after corn were much smaller for biotech corn hybrids.

[2]The data are from confidential crop insurance records that span the 1995-2012 period. An non-exhaustive list includes Roberts et al. (2017), Urban, Sheffield, and Lobell (2015), Seifert, Roberts, and Lobell (2017), and Lobell et al. (2014).

[3]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.

[4]Butler and Huybers (2012) demonstrate that corn has adapted to local temperatures, suggesting the potential for future adaptation to hot temperatures.

[5]Kolstad and Moore (2019) note that such analyses of long-run weather trends may suffer from identification biases if climate changes are correlated with trends in technology.

[6]An anonymous referee notes that this may raise questions regarding the endogenous adoption of biotech corn hybrids in that adoption may be associated with other unobservable farm and grower characteristics. We view this concern as pertaining to the definition of the endogenous variable of interest and in how one should frame our inferences. As noted, we readily acknowledge the likely existence of such differences but view our inferences as applying to the adoption of biotech hybrids as well as all of the other differences that may be associated with adoption (e.g., producer ability, farm characteristics, etc.). Any analysis based on data aggregated over time or across individuals is subject to the same limitations. As we note below, all of our explanatory factors are predetermined relative to the realized differences in risk, as reflected in crop insurance outcomes.

[7]Program costs were taken from unpublished USDA Risk Management Agency data.

[8]It should be noted that not all biotech corn hybrids are the same. Biotech traits can be broadly grouped into four types: herbicide resistance, above-ground insect (corn-borer) resistance, below-ground insect (root worm) resistance, and 'stacked' hybrids that combine multiple traits. The BE was only available for triple (or greater) stacked trait hybrids. Such stacked trait hybrids may contain up to eight traits, each having different proteins that target insects in different ways. Stacked traits are thought to offer higher yields because of potential synergistic effects and a smaller refuge requirement (1998). Only stacked trait hybrids qualified for the BE. According to USDA-ERS (2019) data, about 55% of corn hybrids planted in the US over the BE period were stacked trait varieties.

[9]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.

[10]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.

[11]An online appendix contains a detailed comparison of weather and corn yields in 1988 and 2012. These weather statistics were collected from the National Oceanic and Atmospheric Administration's (NOAA) National Climate Data Center.

[12]Note that the fact that GE adoption went from zero in 1988 to levels ranging from 74-97% (for all traits) in 2012 may complicate precise identification of both a discrete year effect and the effect of GE adoption. With the exception of the bt regression, the estimates that included a year-specific fixed effect had collinearity variance inflation factors and tolerance statistics that exceeded the values that Belsley, Kuh, and Welsch (1980) suggest indicate significant losses in numerical precision. We have provided strong evidence that the 1988 and 2012 droughts were of similar intensity. Results that include the discrete 2012 indicator should be interpreted with this caveat in mind.

[13]Insurance units represent different levels of aggregation. A farmer can choose to insure all units (somewhat analogous to individual fields) together (an enterprise unit) or at disaggregated levels (basic and optional units).

[14]The summed BE participation data (total premiums, liabilities, acreage, etc.) were subtracted from the relevant county-level summed totals for all corn policies in order to derive totals for the non-BE policies. A very small proportion of the data, accounting for 1.3% of the observations and 0.02% of the relevant acreage, had negative loss-costs and loss-ratios or had loss-cost ratios that exceeded 1.0. These observations were dropped from the analysis. This occurs in rare cases because of the manner in which sub-unit data are recorded by RMA. The results presented below were virtually identical with respect to whether these data were included or excluded.

[15]We also considered a complete breakout by unit and practice type. Irrigation of corn is relatively rare in the Corn Belt and unit divisions are relatively homogeneous. Results obtained by this finer decomposition were qualitatively identical to those presented here.

[16]Note that this expression assumes identical fixed year and cross-sectional effects. Relaxing this assumption suggests an intercept term γ_0 that could vary in the cross-section or over time. We considered a version with fixed county and year effects. The results are very similar and are available in an online appendix.

[17]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.

[18]We considered an alternative specification that replaced the crop condition variable with the July values of Palmer's Z drought index, which is certainly exogenous to realized crop insurance outcomes. The implications of our analysis were consistent with this specification. These estimates are available in an online appendix.

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

[20]The systemic nature of losses within a county suggests that weighting by size and scale may distort inferences. Our approach also avoids the inferential problems associated with tests of differences in means with alternative weights.

[21]This resulted in about 19% of the observations being omitted from the analysis. As a referee notes, this means that our inferences are conditional on a BE or non-BE indemnity occurring. Results for the entire sample, including cases where no indemnities were paid on either BE or non-BE policies, are included in an online appendix.

[22]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.

[23]As we have noted, all of our explanatory variables are predetermined, alleviating concerns regarding endogenity biases. Adopters may differ from adopters in unobservable ways and thus that our dependent variable measures not just biotech adoption but all of the other differences that may exist between BE and non-BE farmers. To the extent that these latent factors develop along with biotech adoption, the results remain relevant for looking at future yields and drawing inferences regarding the future responses of yields to changing climate conditions.

[24]Many growers chose to shift coverage to enterprise units at a higher coverage level in response to the higher subsidy. 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.

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

[26]This same general confounding of multiple, overlapping changes in technology and associated factors is inherent in all of the aforementioned studies that rely on passively-observed (non-experimental) data. A

fixed experiment whereby such factors are assigned randomly to different plots, seems the only realistic way to discern the effects of individual components of the overall technology treatments.

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

Parameter	Estimate	Het-Consistent Std. Error	t Ratio	NOAA Div Clustered Std. Error	t Ratio	F Statistic	R^2
Stacked Trait Adoption							
Intercept	−0.4578	0.0129	−35.39*	0.0339	−13.54*	49.37*	0.027
Stacked Trait Adoption	0.0026	0.0004	7.08*	0.0009	2.93*		
Bt Trait Adoption							
Intercept	−0.4710	0.0127	−37.18*	0.0318	−14.85*	83.25*	0.044
Bt Trait Adoption	0.0123	0.0015	8.37*	0.0038	3.28*		
Herbicide Tolerant Adoption							
Intercept	−0.4701	0.0128	−36.61*	0.0340	−13.85*	73.50*	0.039
Herbicide Tolerant Adoption	0.0084	0.0010	8.57*	0.0024	3.48*		
All GM Adoption							
Intercept	−0.4671	0.0130	−35.95*	0.0340	−13.75*	64.80*	0.035
All GM Adoption	0.0018	0.0002	7.89*	0.0006	3.19*		
Stacked Trait Adoption							
Intercept	−0.4654	0.0130	−35.74*	0.0340	−13.70*	40.30*	0.043
Stacked Trait Adoption	−0.0101	0.0020	−5.19*	0.0050	−2.01*		
2012 Indicator	0.6975	0.1073	6.50*	0.2799	2.49*		
Bt Trait Adoption							
Intercept	−0.4654	0.0130	−35.74*	0.0340	−13.70*	43.21*	0.046
Bt Trait Adoption	0.0183	0.0041	4.44*	0.0085	2.32*		
2012 Indicator	−0.0952	0.0561	−1.70	0.1712	−1.35		
Herbicide Tolerant Adoption							
Intercept	−0.4654	0.0130	−35.74*	0.0340	−13.70*	39.98*	0.042
Herbicide Tolerant Adoption	0.0197	0.0036	5.44*	0.0085	2.32		
2012 Indicator	−0.2317	0.0732	−3.17*	0.1712	−1.35		
All GM Adoption							
Intercept	−0.4654	0.0130	−35.74*	0.0340	−13.70*	35.01*	0.037
All GM Adoption	0.0077	0.0024	3.24*	0.0057	1.34		
2012 Indicator	−0.5191	0.2048	−2.53*	0.4909	−1.06		

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

Table 2: Variable Definitions and Summary Statistics[a]

Variable	Definition	Mean	Standard Deviation
LCR Difference	Difference in loss-cost ratio between BE and non-BE policies	0.02820	0.11097
LR Difference	Difference in loss-ratio between BE and non-BE policies	0.16192	1.13290
LCR BE	Loss-cost ratio for BE policies	0.04293	0.09913
LCR Non-BE	Loss-cost ratio for non-BE policies	0.07114	0.12034
Acres BE	Acres insured on BE policies	4,604.74	7,494.06
Acres Non-BE	Acres insured on non-BE policies	14,099.40	18,120.70
Liability BE	Total liability insured on BE policies	2,815,484.17	4,985,054.19
Liability Non-BE	Total liability insured on non-BE policies	8,088,137.43	11,588,290.93
Premium BE	Total premium on BE policies	202,895.21	338,378.53
Premium Non-BE	Total premium on non-BE policies	737,757.30	1,025,790.42
Indemnities BE	Total indemnities on BE policies	69,278.29	192,933.46
Indemnities Non-BE	Total indemnities on non-BE policies	424,694.95	1,052,635.09
Premium Rate BE	Premium rate on BE policies	0.08903	0.04486
Premium Rate Non-BE	Premium rate on non-BE policies	0.10539	0.05069
Emerged	Percentage of corn crop emerged by week 20	42.18483	26.97338
Silking	Percentage of corn crop silking by week 30	72.96916	22.48589
Poor Condition	Percentage of crop rated fair, poor, or very poor	35.79601	12.00594
Stacked Trait Adoption	Percentage of acres planted to stacked trait corn hybrids	50.54008	8.43698
Price-Based Loss	Proportion of losses attributed to price declines	0.06779	0.15946
APH Yield	Previous 10 year average of APH yields	145.19654	23.13477
Historical LCR	Previous 10 year average of LCR	0.06441	0.07399
Coverage Level	Average Coverage Level	0.74026	0.07480

[a] Number of observations is 8,859.

Table 3: Summary Statistics: Weighted Conditional Means for (BE vs. No BE) LCR and LR Differences[a]

Category	N	LCR Difference	LR Difference	Rate Difference
Aggregate Sample				
All	36,906	0.0274	0.2310	0.0192
By Coverage Level				
0.50	939	0.0149	0.1828	0.0224
0.55	182	0.0318	0.4836	0.0138
0.60	757	0.0297	0.1490	0.0472
0.65	5,454	0.0226	0.2411	0.0174
0.70	8,769	0.0310	0.2312	0.0255
0.75	9,681	0.0338	0.2829	0.0227
0.80	7,057	0.0249	0.2112	0.0182
0.85	4,067	0.0150	0.1236	0.0110
By Year				
2008	5,907	0.0134	0.0318	0.0130
2009	11,190	0.0153	0.1044	0.0252
2010	10,648	0.0282	0.2331	0.0232
2011	9,161	0.0233	0.2093	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	8,000	0.0257	0.2525	0.0142
Kansas	1,216	0.0011	−0.0699	0.0183
Michigan	875	0.0203	0.1760	0.0068
Minnesota	5,125	0.0291	0.2554	0.0200
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	3,547	0.0060	0.0179	0.0115
NON-IRR	33,359	0.0292	0.2477	0.0198
By Unit Structure				
BU	14,758	0.0246	0.2265	0.0149
EU	9,265	0.0211	0.2060	0.0163
OU	12,883	0.0272	0.1901	0.0182
By Plan				
RP	30,157	0.0284	0.2345	0.0199
YP	6,749	0.0072	0.0752	0.0107

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

Table 4: Summary Statistics: Unweighted Conditional Means for (BE vs. No BE) LCR and LR Differences[a]

Category	LCR Difference	t Statistic	LR Difference	t Statistic	Rate Difference	t Statistic
Aggregate Sample						
All	0.0285	30.11	0.1299	11.27	0.0159	89.60
By Coverage Level						
0.50	0.0677	4.95*	0.8564	2.67*	0.0255	8.55*
0.55	0.0785	2.05*	0.5818	0.86	0.0409	2.51*
0.60	0.0956	5.27*	0.4755	2.13*	0.0373	10.33*
0.65	0.0318	11.04*	0.1560	3.22*	0.0174	31.28*
0.70	0.0278	14.07*	0.1278	5.23*	0.0175	48.39*
0.75	0.0282	17.67*	0.1168	6.51*	0.0159	54.92*
0.80	0.0254	12.85*	0.1067	6.09*	0.0137	42.25*
0.85	0.0237	8.70*	0.0864	3.79*	0.0127	22.30*
By Year						
2008	0.0119	6.95*	−0.0481	−1.54	0.0115	44.36*
2009	0.0211	11.53*	0.0854	4.08*	0.0184	44.20*
2010	0.0350	18.12*	0.1641	7.00*	0.0178	55.28*
2011	0.0394	20.99*	0.2488	13.04*	0.0146	42.91*
By State						
Colorado	0.0083	0.57	0.0317	0.30	0.0212	7.21*
Illinois	0.0262	14.76*	0.1190	4.16*	0.0159	35.03*
Indiana	0.0337	13.54*	0.1924	7.72*	0.0185	36.46*
Iowa	0.0093	5.51*	−0.0815	−2.64*	0.0130	71.82*
Kansas	0.0136	2.26*	0.0427	0.82	0.0148	11.61*
Michigan	0.0372	4.56*	0.1872	2.33*	0.0154	11.84*
Minnesota	0.0254	11.84*	0.1896	7.96*	0.0155	34.41*
Missouri	0.0510	5.23*	0.1812	2.39*	0.0204	11.29*
Nebraska	0.0082	2.75*	0.0035	0.09	0.0123	24.40*
Ohio	0.0476	11.19*	0.3793	10.19*	0.0141	25.73*
South Dakota	0.1105	18.77*	0.6247	15.78*	0.0267	29.70*
Wisconsin	0.0217	4.88*	0.1185	3.53*	0.0165	11.89*
By Practice						
IRR	0.0266	5.52*	0.1026	1.81	0.0132	26.88*
NON-IRR	0.0287	30.44*	0.1322	11.47*	0.0162	85.86*
By Unit Structure						
BU	0.0308	18.99*	0.1248	5.72*	0.0169	59.25*
EU	0.0294	16.18*	0.2254	11.76*	0.0107	39.73*
OU	0.0256	17.04*	0.0737	4.28*	0.0183	56.17*
By Plan						
RP	0.0289	28.96*	0.1390	14.66*	0.0161	83.06*
YP	0.0261	9.13*	0.0736	1.27	0.0151	33.71*

[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: BE and Non-BE Loss-Cost and Loss-Ratio Difference (BE vs. No BE) Regressions (Coverage Level/County/Year Aggregation)[a]

Parameter	Estimate	Het-Consistent Std. Error	t Ratio	NOAA Div Clustered Std. Error	t Ratio
loss-cost Regressions					
Intercept	0.01171	0.00398	2.94**	0.00856	1.37
Poor Condition	0.00047	0.00011	4.19**	0.00019	2.41**
N		8,892			
F-Statistic		21.71**			
R^2		0.0024			
Intercept	0.08130	0.02022	4.02**	0.02802	2.90**
Emerged	−0.00028	0.00007	−3.89**	0.00012	−2.32**
Silking	0.00026	0.00009	2.91**	0.00015	1.77*
Poor Condition	0.00045	0.00012	3.70**	0.00017	2.72**
Stacked Trait Adoption	0.00135	0.00018	7.69**	0.00036	3.73**
Price-Based Loss	−0.02004	0.00453	−4.42**	0.00714	−2.80**
APH Yield	−0.00073	0.00011	−6.45**	0.00016	−4.66**
Historical LCR	0.12749	0.04274	2.98**	0.05855	2.18**
Coverage Level	−0.06100	0.02228	−2.74**	0.02650	−2.30**
N		8,819			
F-Statistic		70.11**			
R^2		0.0590			
Intercept	0.03556	0.03872	0.92	0.05520	0.64
Poor Condition	0.00353	0.00114	3.08**	0.00132	2.67**
N		8,892			
F-Statistic		12.33**			
R^2		0.0013			
Intercept	0.75297	0.25179	2.99**	0.27771	2.71**
Emerged	−0.00290	0.00077	−3.78**	0.00105	−2.76**
Silking	0.00332	0.00094	3.53**	0.00114	2.92**
Poor Condition	0.00296	0.00127	2.32**	0.00142	2.08**
Stacked Trait Adoption	0.00747	0.00139	5.37**	0.00245	3.05**
Price-Based Loss	−0.26537	0.06015	−4.41**	0.07993	−3.32**
APH Yield	−0.00307	0.00109	−2.80**	0.00132	−2.33**
Historical LCR	0.48584	0.34740	1.40	0.40899	1.19
Coverage Level	−1.02853	0.35622	−2.89**	0.29532	−3.48**
N		8,819			
F-Statistic		22.88**			
R^2		0.0195			

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

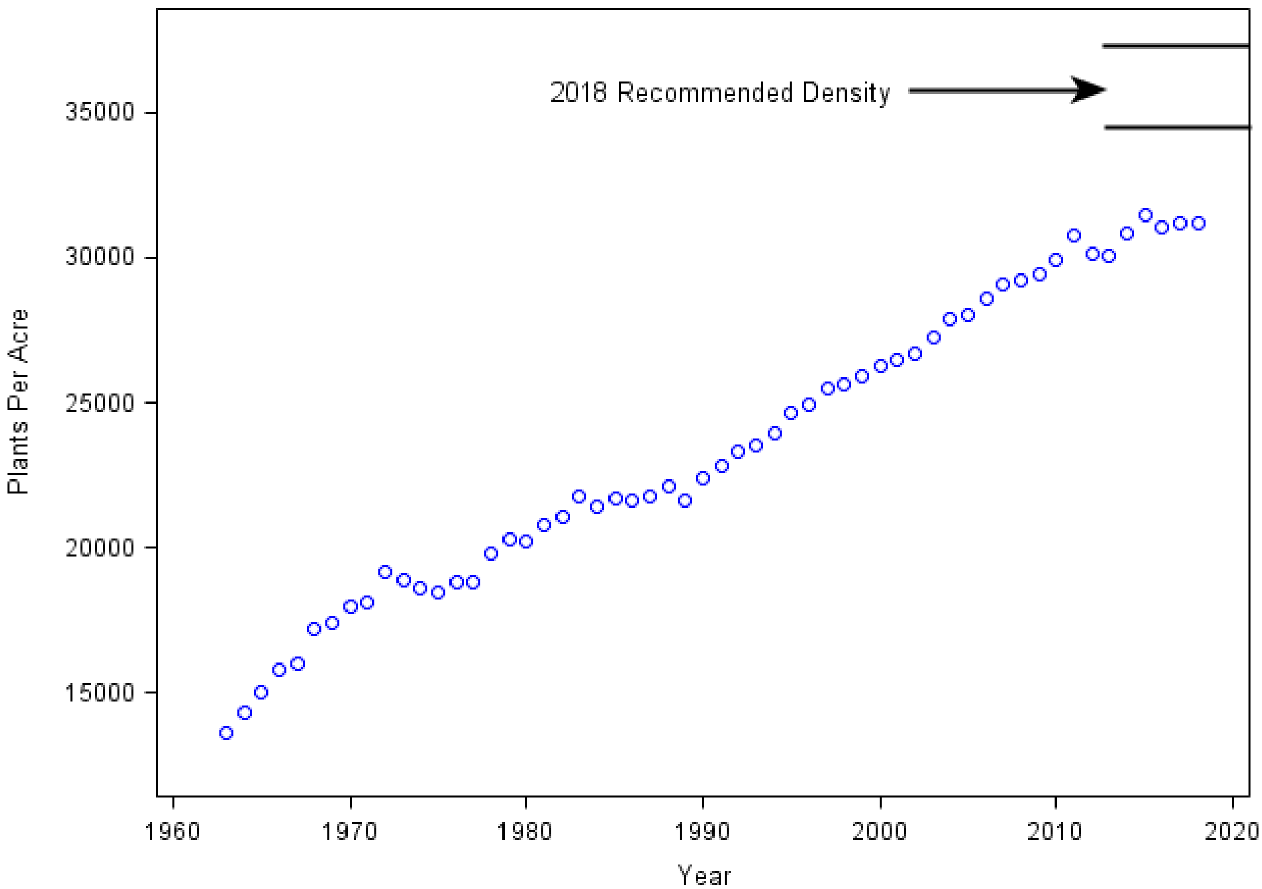


Figure 1: USDA-NASS Average Corn Planting Density in Iowa with ISU Extension 2018 Recommended Range

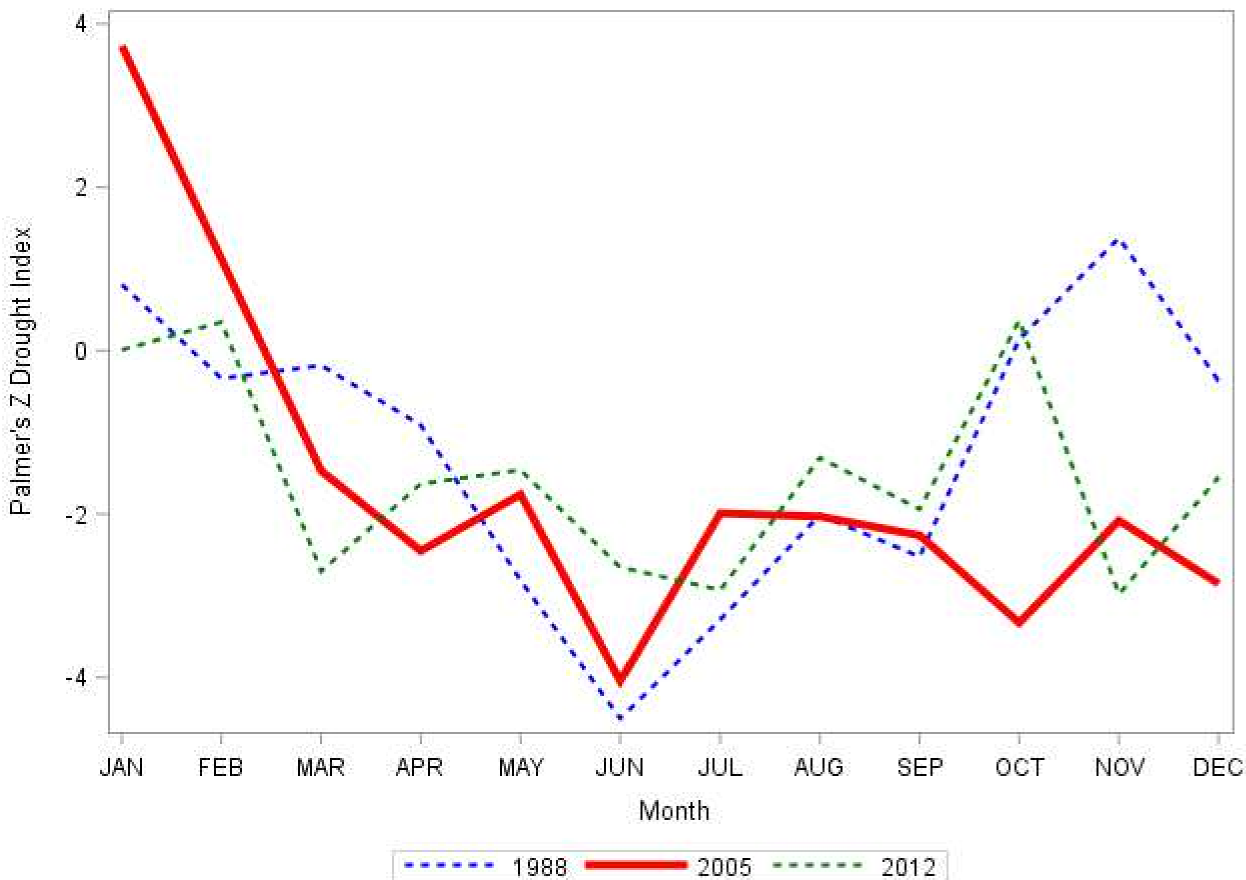
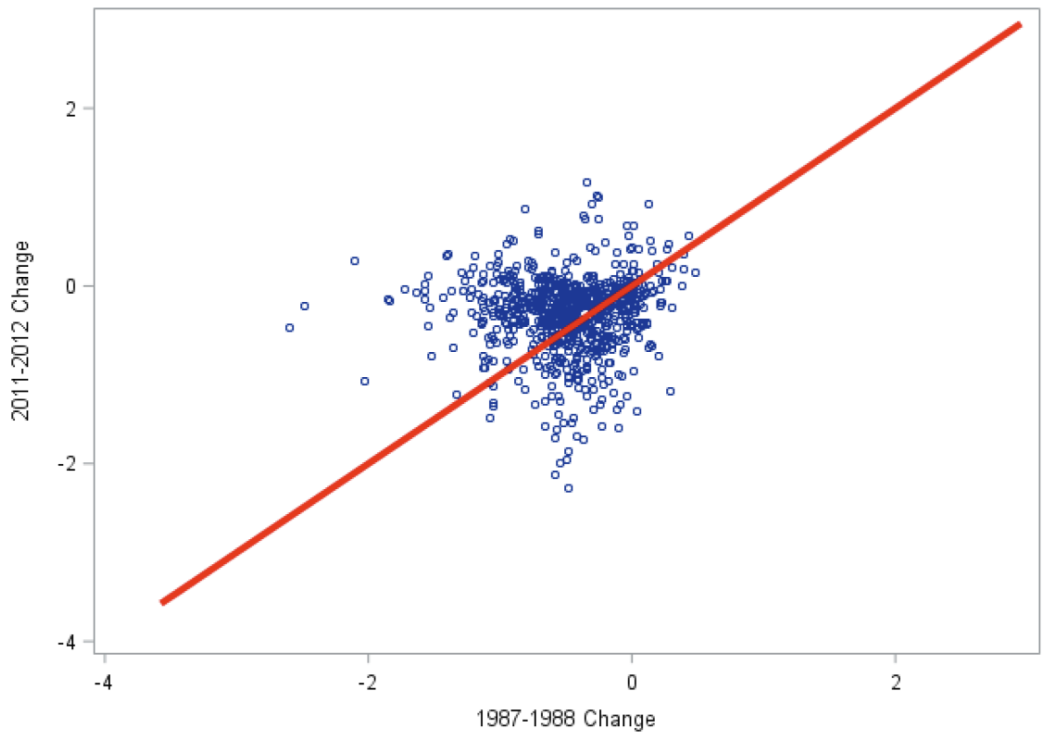
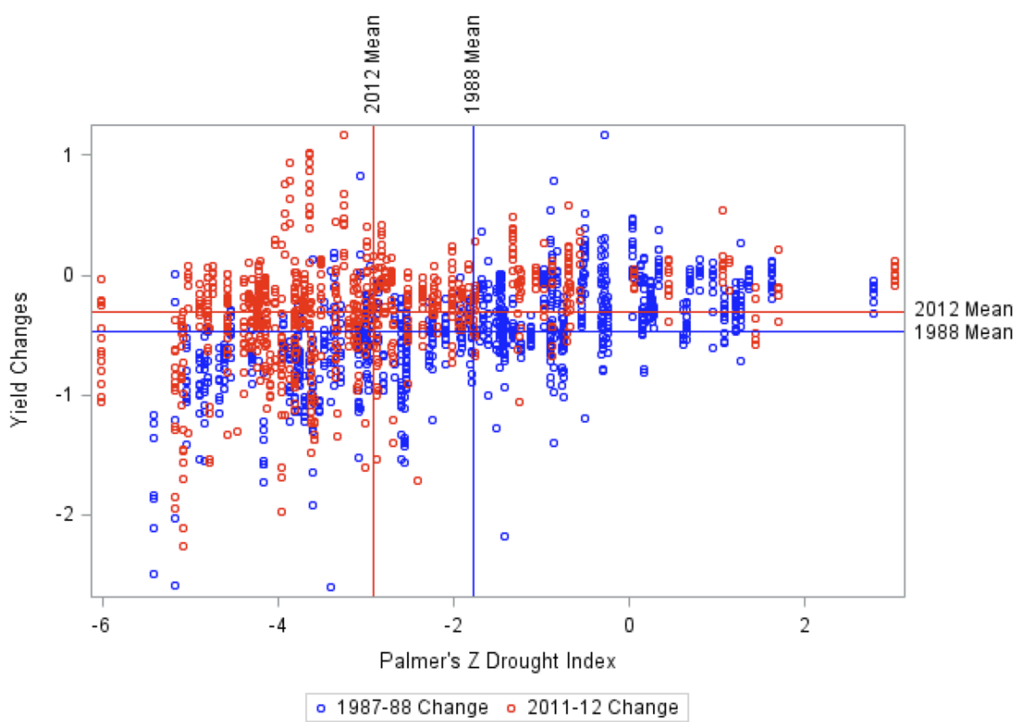


Figure 2: Palmer's Z Drought Index: Northeast Illinois

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.)

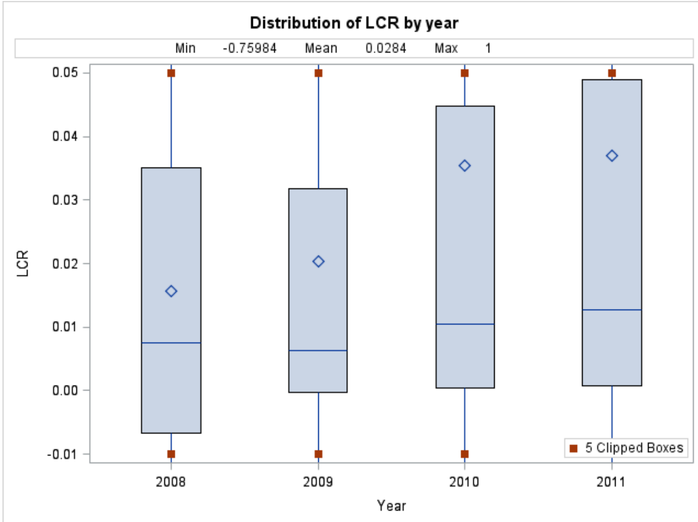


(a) 1987/1988 and 2011/2012 Corn Yield Changes

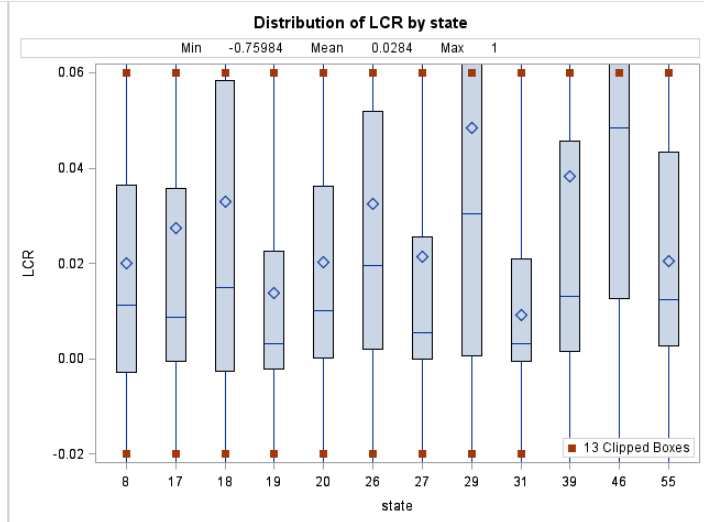


(b) Yield Changes and the Palmer Z Drought Index

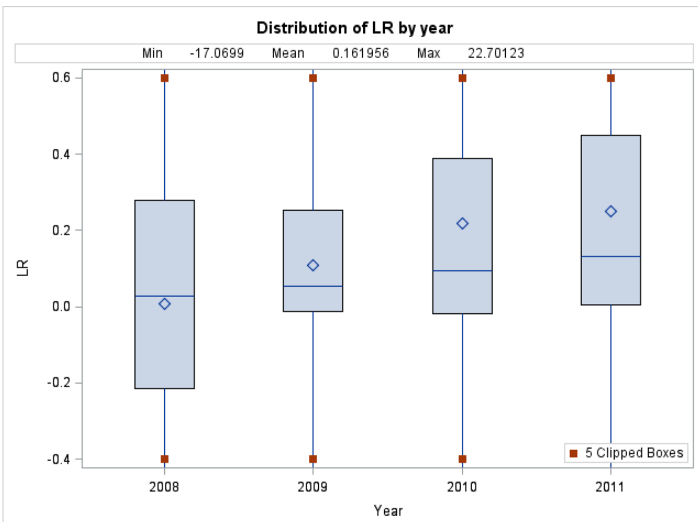
Figure 4: Yield Changes and Drought Conditions in 1988 and 2012



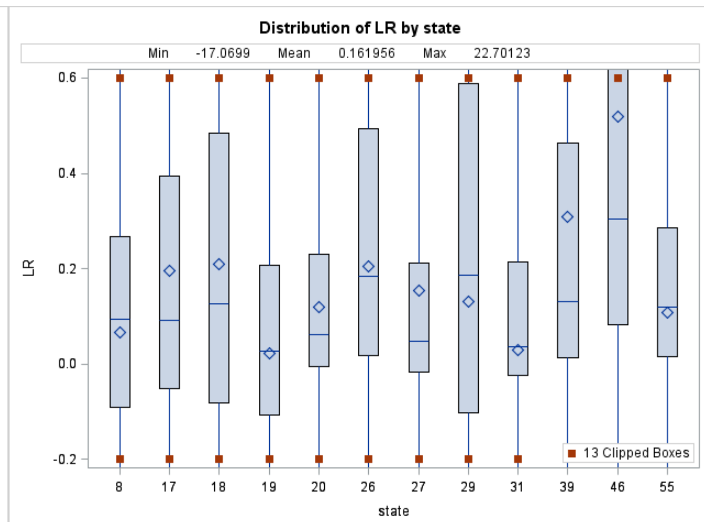
(a) LCR Difference by Year



(b) LCR Difference by State



(c) LR Difference by Year



(d) LR Difference by State

Figure 5: Distributions of LCR and LR by Year and State

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