Yield benefits of drought-tolerant varieties in U.S. maize production

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Abstract

Drought-tolerant varieties are widely regarded as a critical strategy for safeguarding food production against drought under climate change. However, whether their yield advantages observed in field trials are realized in commercial production remains unclear, due largely to a lack of empirical evidence. Using a large-scale dataset on seed usage in U.S. maize production, we show that drought-tolerant maize varieties reduce drought-related yield risk in western Corn Belt counties—with generally stronger effects under more stressful environments—but show limited effects in eastern Corn Belt counties. Additional yield quantile analysis, restricted to rainfed western Corn Belt counties, reveals yield benefits persist across the entire yield distribution, from low- to high-yielding environments, providing evidence against yield penalty concerns under high-yielding conditions. Collectively, these results demonstrate the climate change adaptation value of drought-tolerant maize varieties and position it as a meaningful step toward climate-resilient agriculture—particularly when aligned with supportive insurance structures and regionally adapted deployment strategies.

Introduction

The past decades have seen increases in the frequency and severity of drought occurrences in the United States and globally, undermining agricultural produdctivity and contributing to social instability (Mazdiyasni and AghaKouchak 2015; von Uexkull et al. 2016; Chen et al. 2025). Economically, drought represents the most expensive cause of crop insurance claims in the United States, accounting for roughly half of all indemnity payments (Wallander et al. 2017; Perry et al. 2020). With a changing climate, pervasive and severe droughts are projected in the coming decades (Dai 2013; Christian et al. 2021; Naumann et al. 2021; Pokhrel et al. 2021).

Seed innovation is widely recognized as an adaptation strategy for enhancing drought resilience, with drought-tolerant (DT) varieties in particular holding the potential to become a multibillion-dollar global market (Tollefson 2011). In the United States, drought-tolerant maize varieties became widely available by 2012, followed by drought-tolerant soybeans in 2016. Field trials win

the U.S. Corn Belt have demonstrated yield advantages under water stress conditions (Mounce et al. 2016; Gaffney et al. 2015; Nemali et al. 2015).

Nevertheless, whether the drought-tolerant varieties constitute a climage change adaptation tool in commercial production is yet to answer (Lobell 2014a). Yield gains observed in trial settings may not fully translate to farm-level benefits due to environmental heterogeneity and potential behavioral responses in farm management, such as increased seeding rates (Lobell et al. 2014b). Moreover, yield penalties under optimal growing conditions have been reported, suggesting that varieties designed to perform under drought stress may underperform when water is abundant, possibly due to physiological trade-offs or resource constraints (Lybbert and Bell 2010; Tollefson 2011; Zhao et al. 2015; Lobell et al. 2020; Yu et al. 2021).

Understanding the realized yield performance of drought-tolerant varieties in commercial settings carries important implications for the U.S. Federal Crop Insurance Program (FCIP), which mandates actuarially fair premiums. A relevant precedent is the Biotech Endorsement (BE) program, implemented across the Corn Belt between 2009 and 2012, which provided premium discounts to reflect the reduced yield risk of certain genetically modified hybrids (Goodwin and Piggott 2020).

In this study, we analyze nationally representative, large-scale farm survey data on seed usage, combined with county-level yield and crop insurance records, to assess the yield effects of adopting drought-tolerant maize varieties in U.S. commercial maize production. We examine the extent to which these varieties reduce downside yield risk associated with drought and alter yield distributions, and we explore the resulting implications for crop insurance policy.

Results

Regional heterogeneity in drought-tolerant maize planting, drought exposure and yield risk

Drought exposure is measured using the June-August mean of the U.S. Drought Monitor's Drought Severity and Coverage Index (DSCI), which captures both the spatial extent and severity of drought conditions. Values range from 0, indicating that no part of the area is abnormally dry or in drought, to 500, indicating that the entire area is experiencing exceptional drought. The county-year DSCI data are matched to downside yield risk attributable to drought, measured using the drought-related loss-cost ratio (LCR, in %): the indemnified amount, for which the cause of loss is drought, divided by total liability aggregated at the county level (Goodwin and Piggott 2020; Perry et al. 2020). Data are obtained from the Cause of Loss and Summary of Business databases maintained by the USDA Risk Management Agency.

Drought-tolerant maize varieties are available in both genetically engineered (GE) and non-GE forms. Syngenta first released drought-tolerant hybrids in 2011 as Agrisure Artesian® using molecular breeding, followed by DuPont Pioneer's conventionally bred Optimum AQUAmax®. In parallel, Monsanto, in collaboration with BASF, developed the only commercially marketed genetically engineered (GE) seeds, Genuity DroughtGard®, launched in 2012 and widely available by 2013. These GE hybrids express cold-shock protein B (cspB) to regulate biological functions, via insertion of the corresponding gene from the soil bacterium *Bacillus subtilis*.

Despite its short history, drought-tolerant maize has diffused at a rate comparable to insect-resistant Bt maize and herbicide-tolerant maize (Fig. 1a-b). By 2016, around 17% of maize planting acres in the nationally representative TraitTrak® sample were drought-tolerant: 21% in the western Corn Belt (including North Dakota, South Dakota, Minnesota, Iowa, Missouri, Nebraska, and Kansas) and 11% in the eastern Corn Belt (Illinois, Indiana, Michigan, Ohio, Wisconsin, and Kentucky). Adoption is particularly high in Kansas and Nebraska—drought-prone, maize-producing areas prioritized in the development and marketing of drought-tolerant (DT) seeds (Fig. 1c). Consistent with this focus, most U.S. field trials occur in the drought-prone western Corn Belt (Gaffney et al., 2015). The market share of GE varieties has increased since debut, but conventionally bred varieties dominated the drought-tolerance market during 2013–2016 (Fig. S1).

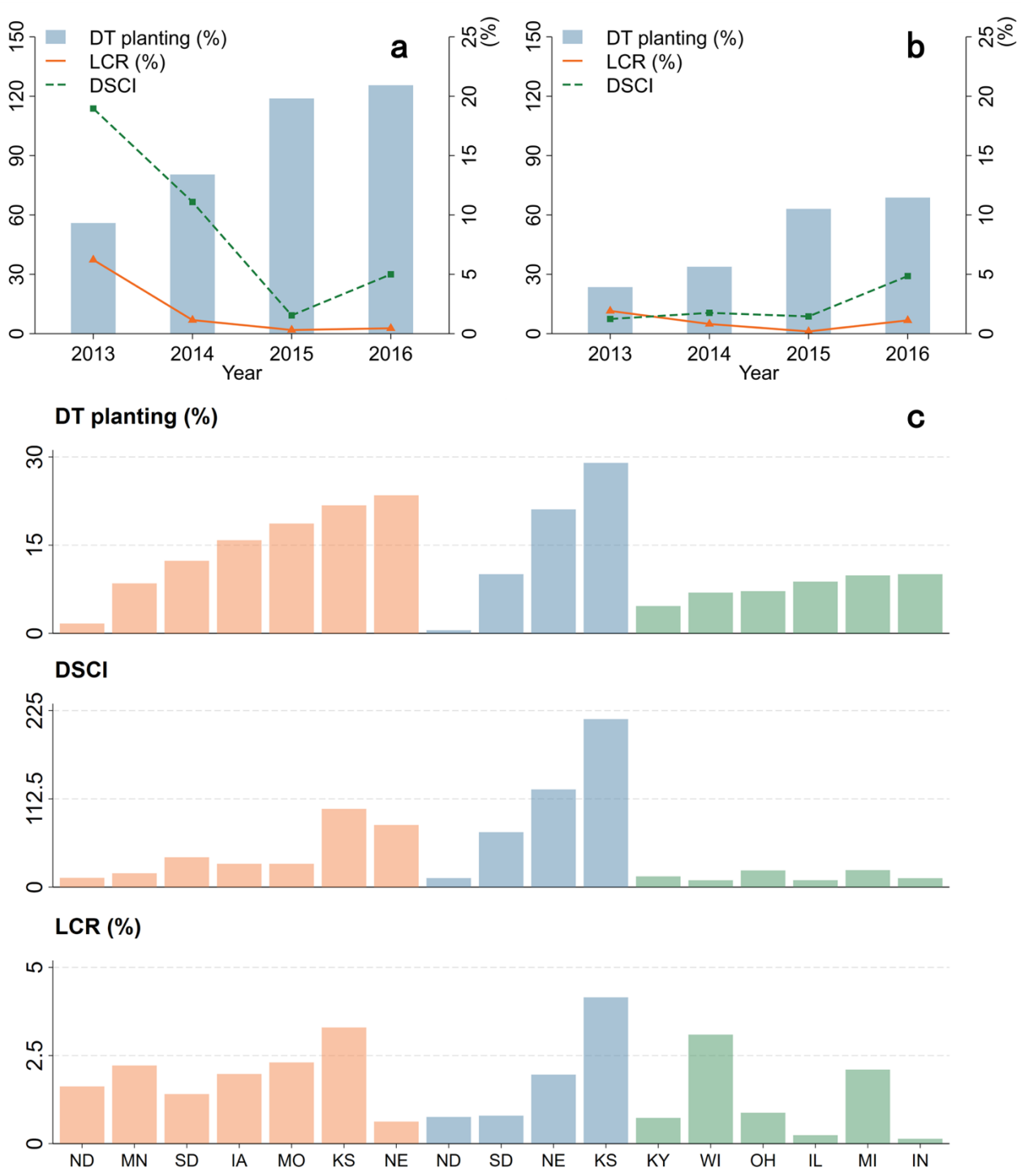


Fig. 1 Temporal changes and spatial heterogeneity of drought-tolerant maize planting (DT planting, in %), drought exposure (DSCI), and drought-related yield risk (LCR, in %) in U.S. maize production. Panels (a) and (b) show time series for the western and eastern Corn Belt counties, respectively; panel (c) depicts spatial heterogeneity, with orange for rainfed western Corn Belt counties (east of the 100th meridian), blue for western non-rainfed western counties, and green for eastern counties (Kansas and Nebraska have both rainfed and non-rainfed countie s in the sample).

DT protection against drought is regionally differentiated

For an initial investigation of the protection conferred by drought-tolerant (DT) varieties, we compare the LCR-DSCI relationship for DT-planting versus non-DT counties during 2013–2016 (Fig. 2). The LCR, transformed via the inverse standard normal cumulative distribution function, is linearly regressed on DSCI to estimate the sensitivity of yield risk to drought intensity. For DT-planting counties in the western Corn Belt (upper panel), kernel density estimates reveal a long-tailed distribution of DSCI values, ranging from 0 to 500, reflecting substantial exposure to drought. In contrast, non-DT counties experienced markedly milder conditions, with DSCI values not exceeding 200. For eastern Corn Belt (bottom panel), greater density at lower DSCI for both DT and non-DT counties likewise indicates that, overall, the eastern Corn Belt was less affected by drought than the western.

Importantly, while yield risk rises with drought in both DT-planting and non-DT counties, the LCR–DSCI slope is smaller for DT-planting counties than for non-DT counties in the western Corn Belt, indicating an attenuated yield risk response and measurable protection from DT varieties against drought-related losses, and DT benefits scale with environmental stress. This observed mitigation is consistent with the intended physiological and agronomic benefits of DT hybrids, particularly in the high-exposure environments of the western Corn Belt. In the eastern Corn Belt, however, the slope is larger for DT-planting counties. Although initially counterintuitive, this pattern aligns with contemporary breeding and selection: DT hybrids have been tailored to western environments through years of field trials, and currently marketed products may be less agronomically suited to eastern conditions. Overall, the evidence indicates regional heterogeneity—during the study period, measurable benefits accrue in the western Corn Belt but not in the east.

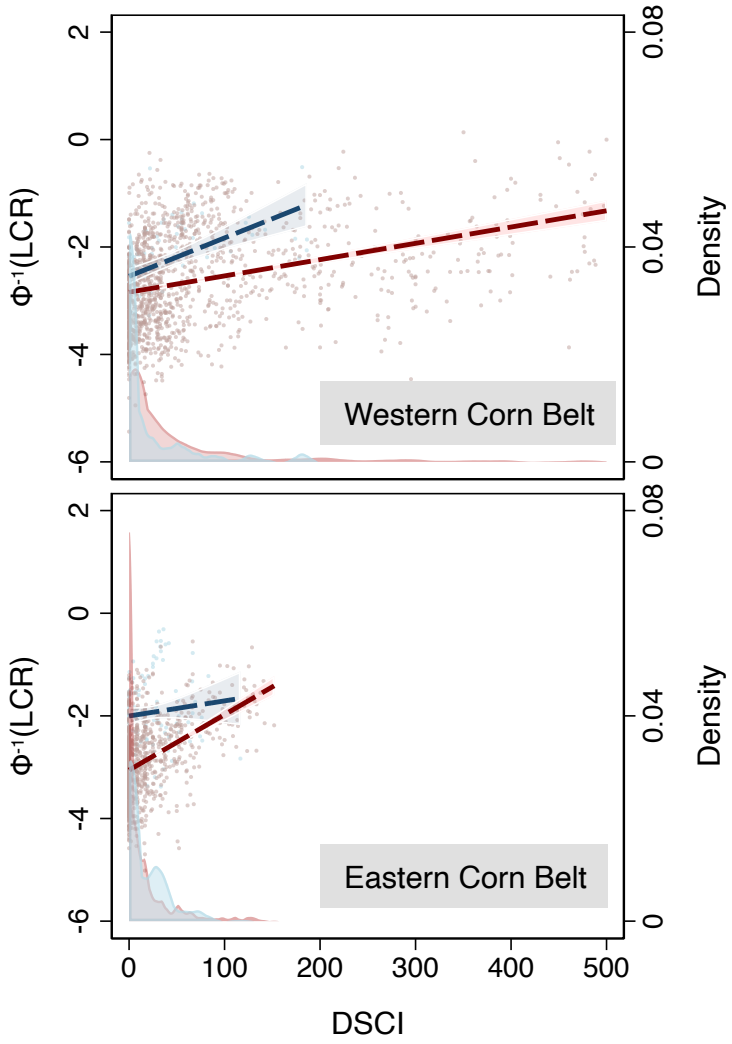


Fig. 2 Drought-yield risk relationship for DT-planting versus non-DT counties in the western (upper panel) and eastern (lower panel) Corn Belt. The DT and non-DT subsamples are shown in red and blue, respectively. The dots represent county-year observations in the subsample spanning 2013 to 2016; dashed lines are linear fits of drought-related yield risk (LCR; transformed using the inverse standard normal cumulative distribution function) on the drought measure ($DSCI$). Shaded bands indicate 95% confidence intervals. Shaded areas at the bottom of each panel show kernel densities of $DSCI$.

The first set of regression analysis uses fractional response model to estimate the average partial effects (APE) of higher DT planting rates on yield risk response to drought levels (Papke and Wooldridge 1996; see Methods for more details). Regression analysis allows to address confounding factors associated with unobserved county heterogeneity through applying correlated random effects approach (Papke and Wooldridge 2008), and year fixed effects to eliminate time-specific unobservable confounding factors. Climatic controls, growing degree days (GDD) and stress degree days (SDD), are also included to capture heat effects (Tack et al. 2015).

At DSCI = 0 (no drought), the DT-attributable difference in yield risk is not statistically different from zero, conditional on observed controls and unobserved effects (Table 1, Model (1)). However, the significantly negative estimates for $DT \times DSCI$ interaction term indicates that yield risk reduction from DT increases with drought exposure, consistent with the adaptive value of the technology and with the preceding section's finding that DT benefits scale with environmental stress. Although specification in Model (1) likely accounts for most confounding, we additionally control for trait stacking—measured as the planting rate of first-generation GE seeds (insect-resistant Bt and herbicide-tolerant traits; GE1, %)—in Model (2); results closely match the main specification, indicating that the baseline controls are adequate. Restricting the sample to rainfed areas yields similar results (Model (3)–(4)). In the eastern Corn Belt, however, the interaction terms are significantly positive (Model (5)–(6)), consistent with the patterns in Fig. 2.

Table 1 Fractional response model estimation results (APEs), by region

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
	Western Corn Belt		Western Corn Belt, rainfed only		Eastern Corn Belt	
	Main specification	Stacking controlled	Main specification	Stacking controlled	Main specification	Stacking controlled
DT	0.062	0.018	-0.003	-0.040	-0.113	-0.113
	(0.85)	(0.26)	(-0.05)	(-0.58)	(-1.25)	(-1.27)
$DSCI$	0.019***	0.021***	0.016***	0.017***	0.011***	0.011***
	(4.66)	(5.36)	(3.97)	(4.28)	(3.56)	(3.53)
$DT \times DSCI$	-0.079***	-0.080***	-0.081***	-0.079***	0.311***	0.311***
	(-3.08)	(-3.40)	(-2.97)	(-3.06)	(3.54)	(3.56)
SDD	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***
	(7.40)	(7.41)	(7.31)	(7.14)	(7.23)	(7.22)
$DT \times SDD$	0.001	0.001*	0.002**	0.002***	-0.002	-0.002
	(1.42)	(1.79)	(2.50)	(2.92)	(-0.61)	(-0.62)
GDD	0.000**	0.000***	0.000	0.000*	-0.000	-0.000
	(2.20)	(2.59)	(1.26)	(1.91)	(-1.11)	(-1.08)
$GE1$		0.089***		0.090***		-0.001
		(3.41)		(3.55)		(-0.07)
Observations	6448	6448	5552	5552	5680	5680
Pseudo R^2	0.26	0.27	0.28	0.28	0.25	0.25

Notes: t statistics in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. Year-fixed effects are included, and county-level unobserved heterogeneity is controlled. Standard errors are clustered at the CRD level. In regressions, $DSCI$, DT, and $GE1$ are rescaled by 1/100 for the purpose of presentation.

Persistent protection from low- to high-yielding environment in the western Corn Belt justifies premium discounts

Restricting attention to rainfed counties in the western Corn Belt, we estimate quantile regressions to characterize the yield effects of DT technology across the full distribution of yield conditions—from least to most favorable environments—conditional on county-level unobserved heterogeneity, time trends, and other covariates. Results in Fig. 3 (left panel) show that DT coefficients are statistically positive across all quantiles (1st–99th), including the highest-yielding tail. This pattern counters the yield-penalty hypothesis: under favorable conditions there are no statistically significant negative yield effects; instead, a positive—albeit modest—benefit is retained. Moreover, coefficient magnitudes generally increase toward lower quantiles (i.e., from favorable to unfavorable environments), reaffirming the adaptive value of DT technology.

These findings align with Syngenta's 2012 on-farm strip trials, which reported a generally decreasing yield difference between DT and non-DT varieties as the yield environment improves. At the 1st quantile (lowest-yielding environment), a 10% increase in DT planting within a county is associated with a 17 bu/acre yield gain. Correspondingly, the CDF of yield under 10% higher DT planting shifts rightward uniformly across the distribution in response to positive coefficients, with the largest shift occurring around the 20th percentile (Fig. 3, middle panel). The changes in the yield distribution imply an increase in mean yield as well as a decrease in yield risk as measured by variance. Specifically, probability densities are lower for yields below around 120 bu/acre and higher for yields greater than it (Fig. 3, right panel). Shifts in the CDF and PDF under 20% and 30% higher DT planting rates are also provided (Figs. S2–S3 in the appendix), along with quantile estimation results controlling for first-generation GE stacking (Fig. S4 in the appendix).

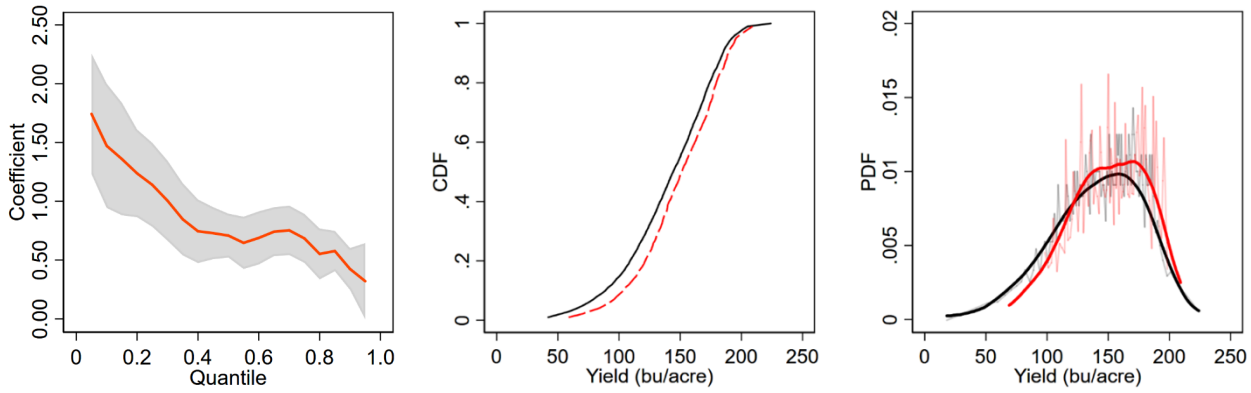


Fig. 3 Effects of drought-tolerant maize planting on the yield distribution in the western Corn Belt. The left panel provides quantile-regression coefficients of DT planting rate (%) across the 1st–99th conditional quantiles. The red line represents point estimates of quantile regression, and the shaded areas represent the 95% confidence intervals. Standard errors are obtained by bootstrapping. The middle and right panels show shift in the cumulative distribution function (CDF) and corresponding shift in the probability density function (PDF) of yield, respectively, under the status-quo (in black) and a 10% increase in DT planting rate (in red). The PDF is approximated as $CDF(x2) - CDF(x1)/(x2 - x1)$ where $x1$ and $x2$ are such that $CDF(x2) - CDF(x1)$ is 0.01. The approximations (the light black and red lines in panel (c)) are then fitted using kernel density estimation to obtain smooth PDF functions for illustration purposes.

We next evaluate the insurance value of DT adoption by simulating changes in actuarially fair premiums under a 10% increase in DT planting (see Methods for more details), using the yield distributions estimated in Fig. 3. We restrict attention to yield insurance policies, whch cover yield risks by guaranteeing a base yield depending on the farmer-chosen coverage level and average production history (APH).

Two countervailing forces emerge. First, a 10% DT increase raises mean yield from 138 to 140 bu/acre (the mean-increase effect), which elevates the yield guarantee and higher actuarially fair premium as it becomes easier to trigger indemnity payment. Second, a distributional shift moves probability mass away from low yields while maintaining the same mean yield (the risk-reduction effect), reducing expected indemnities. Empirically, this risk-reduction effect dominates: actuarially fair premiums fall by 36.92–63.47% across coverage levels (Table 2), with larger percentage reductions at lower coverage levels; the average reduction is 46.21%. Taken together, these results provide a clear rationale for premium discounts to DT adopters.

Table 2 Simulations for actuarially fair premium under status-quo and a 10% DT increase

Coverage level (φ)	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90
Premium, status-quo ($\bar{r}^0$)	1.00	1.24	1.72	2.33	3.18	4.11	5.54	7.11	9.27
Premium, 10% increase in DT ($\bar{r}^1$)	0.36	0.54	0.81	1.24	1.64	2.28	3.16	4.23	5.85
Reduction percentage (%)	63.47	56.60	52.96	46.84	48.50	44.45	43.00	40.44	36.92
Yield guarantee, status-quo	69.04	75.95	82.85	89.75	96.66	103.56	110.47	117.37	124.27
Yield guarantee, 10% increase in DT	70.09	77.10	84.10	91.11	98.12	105.13	112.14	119.15	126.16

Will drought-tolerance technology usher in a new era?

This study presents a comprehensive empirical evaluation of the yield-protective effects of drought-tolerant (DT) technology in commercial maize production across the U.S. Corn Belt. By combining conditional mean analysis of drought-related yield risk and yield quantile analysis, we reveal that DT varieties offer tangible—but spatially heterogeneous—benefits, offering important insights into their potential as a climate adaptation tool and their implications for crop insurance policy.

Most notably, our results suggest that DT performance varies substantially across regions. DT hybrids released between 2013 and 2016 significantly reduce yield risk in the western Corn Belt, and our findings also reinforce the role of DT technology as a climate adaptation innovation, in the strict sense that its benefits increase under more stressful conditions—a critical criterion that

not all agricultural technologies meet (Lobell 2014). In contrast, they exhibit limited effects in the eastern Corn Belt. This heterogeneity reflects breeding strategies that priorized adaptation to western growing conditions, where drought is more frequent and severe. It also underscores a broader truth in agricultural innovation: that biophysical context matters. Technologies developed for one agroecological zone may not be readily transferable to another. As seed companies tailor products to local conditions, policy interventions aimed at accelerating technology diffusion must also account for spatial variability in both agro-environmental conditions and economic incentives.

Focusing on rainfed areas in the western Corn Belt, the yield quantile analysis finds no evidence of a yield penalty associated with DT hybrids; rather, modest yield gains are observed even in the highest-yielding environments. This outcome is particularly relevant given concerns that drought-tolerant traits might compromise yield potential under favorable conditions due to physiological trade-offs. The absence of such a trade-off suggests that adoption can still be rational even in the absence of a guaranteed stress event in a given season, making DT hybrids attractive as a preventive rather than purely reactive risk management strategy, particularly in light of rising seed costs, making the learning and technology diffusion process easier than previously believed (Lybbert and Bell 2010).

One important dimension is the integration of DT adoption into the structure of the U.S. Federal Crop Insurance Program. Our simulation results show that broader adoption of DT varieties would lead to significant reductions in actuarially fair premiums, with 10% higher adoption leads to decreases in actuarially fair premium ranging from 36.92 percent to 63.47 percent, emphasizing the need for a discount scheme similar to the Biotech Endorsement program introduced between 2009 and 2012. If the insurance premium fails to reflect the risk reductions associated with DT, adoption of drought tolerant hybrids will likely be disincentivized, ultimately compromising crop growers' capacity to adapt to drought in the long term (Annan and Schlenker 2015; Miao 2020). Furthermore, because the development of DT technologies requires substantial fixed investments—often involving both public and private funding (Lybbert and Carter 2015)—a lack of sufficient market demand could discourage future innovation. Inadequate incentives and adoption may thus constrain not only the diffusion of existing technologies but also future advances in drought-resilient crop development, particularly within the private sector.

Looking forward, drought-tolerant maize varieties represent a meaningful step toward climate-resilient agriculture, particularly when aligned with supportive insurance structures and regionally adapted deployment strategies. Yet their full potential will only be realized through coordinated action across research, policy, and market systems. As climate volatility becomes the new normal, embedding resilience into the seed itself may prove one of the most powerful tools we have.

Methods

Data sources. The analysis in this paper uses data from several different sources to construct a balanced panel at county level, spanning 2001 to 2016. The crop insurance data were obtained from the publicly available Cause of Loss and Summary of Business databases maintained by the USDA Risk Management Agency, which provide the cause-specific claims information and total liabilities by crop annually at the county level.

The DT planting rate (DT, in %) is constructed from a large field-level survey data called TraitTrak®. It is provided by GfK Kynetec, a market research company specializing in the collection of agriculture-related survey data, and is available from 1995 to 2016. The Gfk data products have been used in a number of studies, and previous work has verified the validity of the data (Perry et al. 2016; Ye et al. 2021, 2025). The field-level data are aggregated into the crop reporting district (CRD) level, at which the survey data are representative.

The Drought Severity and Coverage Index (DSCI) given by Drought Monitor is used to assess drought exposure. The U.S. Drought Monitor is a collaborative effort by several organizations and is frequently used by federal agencies in the United States (Kuwayama et al. 2018; Kreibich et al. 2022). More information can be found at: https://droughtmonitor.unl.edu/data/docs/DSCI_fact_sheet.pdf. Since 2001, daily data have been available nationally, and we averaged them from June to August to create the drought variable $DSCI$.

The temperature data comes from the Parameter-elevation Regression on Independent Slopes Model (PRISM) dataset, which is a fine-scale weather dataset for the contiguous United States gridded at 2.5 arc-minute (4 km) resolution. At the county level, two temperature variables are created: stress degree days (SDD) and growing degree days (GDD) for temperatures above 29°C and within 10°C-29°C, respectively, and are averaged across the maize growing season from April to September (Schlenker and Roberts 2009; Perry et al. 2020). Figure S5 depicts the temporal variations in environmental stress and yield risk. It demonstrates that yield risk moves in lockstep with water and heat stress, which often change direction concurrently.

Fractional response regression analysis. Given its proportional nature, the yield risk factors are best modeled as a fractional response, as illustrated in Fig. 2 (Papke and Wooldridge 1996). The fractional response model is specified as follows:

$$E(y_{i,t}|\boldsymbol{x_{i,t}}) = \Phi\begin{pmatrix}\alpha DT_{r[i],t} + \beta_1 DSCI_{i,t} + \beta_2 SDD_{i,t} \\ +\gamma_1 DT_{r[i],t} \times DSCI_{i,t} + \gamma_2 DT_{r[i],t} \times SDD_{i,t} + \theta GDD_{it}\end{pmatrix} \quad (1)$$

where the conditional mean of yield risk $y_{i,t}$ (i for county and t for year) is specified as a probit function, and $\Phi(\cdot)$ denotes the standard normal cumulative distribution function. The explanatory variables are defined as above. We also included year-fixed effects δ_t to eliminate year-specific unobservable factors affecting yield risk, such as other unobserved climatic factors. The year-fixed effects are preferred over time trends because yield risk, unlike yield, fluctuates in nature. In order to control for county-specific unobserved heterogeneity, the correlated random effect (CRE) approach is applied (Papke and Wooldridge 2008). Specifically, rewrite the above equation so that the unobserved county effect enters additively, as follows:

$$E(y_{i,t}|\boldsymbol{x_{i,t}}, c_i) = \Phi(\boldsymbol{x_{i,t}}\boldsymbol{\pi} + c_i). \quad (2)$$

As commented in Papke and Wooldridge (2008), although alternative functional forms such as logistic function in place of the standard normal CDF are possible, the probit function has computational advantages when the time-constant unobserved effect is involved. A conditional normality assumption is further imposed:

$$c_i = \vartheta + \bar{\boldsymbol{x}}_{\boldsymbol{i}}\boldsymbol{\delta} + a_i \quad (3)$$

$$a_i|\boldsymbol{x_i} \sim Normal\ (0, \sigma^2), \quad (4)$$

where $\boldsymbol{x_i} \equiv (\boldsymbol{x_{i,1}}, \boldsymbol{x_{i,2}}, \dots, \boldsymbol{x_{i,T}})$, and $\bar{\boldsymbol{x}}_{\boldsymbol{i}} \equiv T^{-1}\sum_{t=1}^{T}\boldsymbol{x_{i,t}}$ is time-averages for time-varying covariates. Following that, the conditional mean can be expressed as

$$E\left(y_{i,t}\middle|\boldsymbol{x_{i,t}}, c_i\right) = \Phi\left(\vartheta_a + \boldsymbol{x_{i,t}}\boldsymbol{\pi_a} + \bar{\boldsymbol{x}}_{\boldsymbol{i}}\boldsymbol{\delta_a}\right), \quad (5)$$

where the subscripts denote the corresponding original parameters rescaled by $(1 + \sigma^2)^{-1/2}$, for example, $\boldsymbol{\pi_a} = (1 + \sigma^2)^{-1/2}\boldsymbol{\pi}$. So the consistent estimates for average partial effects (APEs) can be obtained by differentiating the following equation with respect to the covariate of interest:

$$N^{-1}\sum_{i=1}^{N}\Phi\left(\hat{\vartheta}_a + \boldsymbol{x_{i,t}}\hat{\boldsymbol{\pi}}_{\boldsymbol{a}} + \bar{\boldsymbol{x}}_{\boldsymbol{i}}\hat{\boldsymbol{\delta}}_{\boldsymbol{a}}\right), \quad (6)$$

where $\hat{\vartheta}_a$, $\hat{\boldsymbol{\pi}}_{\boldsymbol{a}}$, and $\hat{\boldsymbol{\delta}}_{\boldsymbol{a}}$ denote consistent estimates of parameters. For example, the APE estimates for $\boldsymbol{x_{i,t}}$ are given by

$$(NT)^{-1}\sum_{t=1}^{T}\sum_{i=1}^{N}\hat{\boldsymbol{\pi}}_{\boldsymbol{a}}\Phi\left(\hat{\vartheta}_a + \boldsymbol{x_{i,t}}\hat{\boldsymbol{\pi}}_{\boldsymbol{a}} + \bar{\boldsymbol{x}}_{\boldsymbol{i}}\hat{\boldsymbol{\delta}}_{\boldsymbol{a}}\right). \quad (7)$$

An issue that emerges in this context is whether counties with higher DT planting rates systematically differ from those with lower rates and confounds the yield impact. On the demand side, counties with stronger maize yield potential and/or greater drought risk are expected to gain more, making DT technology more likely to be adopted. On the supply side, the drought-prone corn-producing areas are prioritized in developing and marketing DT seeds, leading to higher DT adoption rates are found in the Western Corn Belt, particularly Kansas and Nebraska (Fig. 1). Notably, panel (A) in Fig. S6 shows that during the DT-available years in our sample (2013-2016), DT was almost always stacked with first-generation GE seeds, which had already become ubiquitous by 2012 (a primary reason that BE program ended in 2012); yet Fig. S7 reveals that first-generation GE seeds stacked with DT cost less than first-generation-only seeds, despite a higher retail price. These observations suggest that in DT's early marketing years (2013-2016), seed companies and/or retailers heavily promoted stacked seeds (free units, discounts, etc) to expand the DT market. As a result, DT adoption imposed little to no cost on maize growers during this period, and changes in DT planting were more likely supply-driven. Second, our analysis intends to capture behavioral response to DT adoption in evaluating its empirical value, rather than excluding them. Planting density changes are one example (see Panel (B) in Fig. S6).

Quantile regression analysis. The quantile regression method developed by Koenker and Bassett (1978) generalizes the median regression and applies asymmetric weighting across quantiles (Koenker and Hallock 2001). Given the balanced panel data structure of our sample, the quantile of yield conditional on covariates and unobserved county heterogeneity is given by

$$Q_{y_{i,t}}\left(\tau\middle|\boldsymbol{x_{i,t}}, c_i\right) = \boldsymbol{x_{i,t}}\boldsymbol{\pi}(\boldsymbol{\tau}) + c(\tau)_i, \quad (8)$$

where $y_{i,t}$ denotes yield in county i and year t, the covariate vector $\boldsymbol{x}$ consists of DT planting rate variable, as well as state-specific cubic time trends. Take the DT variable for an example, the coefficient estimate gives the marginal effects of DT on the τ-th conditional yield quantile. The term $c(\tau)_i$, like the conditional mean analysis, represents the time-invariant county heterogeneity at τ-th quantile.

Given the large number of fixed effects, the usual fixed effects model is subject to the incidental parameters problem and thus not suitable for the quantile regression (Lancaster 2000). While methodological progress in this area has been emerging in recent years (Kato et al. 2012; Machado

et al. 2019), they are either computationally difficult to implement, or the consistency of the estimators requires a large number of periods relative to the cross-sectional units. For example, the quantiles via moments estimator proposed by Machado et al. (2019) will be biased for fixed T, and the confidence intervals will have poor coverage where n/T is above 10. Therefore, given the relatively large cross-sectional units (347 counties) and short timespan (2001-2016), we again adopted the Correlated Random Effects (CRE) technique to account for the unobserved heterogeneity (Abrevaya and Dahl 2008).

Simulation of actuarially fair premiums. Let $y \in [0, \infty)$ denote a random yield with cumulative distribution function $F(y)$, and mean value $\bar{y} = E(y)$. Suppose a representative farmer chooses a coverage level $\varphi \in \{0.50, 0.55,\ 0.60, 0.65, 0.70, 0.75, 0.80, 0.90\}$, then a yield level of $\varphi\bar{y}$ is guaranteed. That is, the paid indemnity amount will be $\varphi\bar{y} - y$ when realized yield y is smaller than the yield guarantee $\varphi\bar{y}$, and 0 when the actual yield reaches $\varphi\bar{y}$. The indemnity r can be expressed as

$$r = \max\{\varphi\bar{y} - y, 0\}, \tag{9}$$

and the actuarially fair premium $\bar{r}$ at coverage level φ is

$$\bar{r} = \int_0^{\infty} \max\{\varphi\bar{y} - y, 0\}\, dF(y) = \int_0^{\varphi\bar{y}} (\varphi\bar{y} - y)\, dF(y), \tag{10}$$

which can be rewritten as

$$\bar{r} = \int_0^{\varphi\bar{y}} F(y)\, dy \tag{11}$$

using integration by parts. Graphically, the actuarially fair premium is the area below the CDF $F(y)$ from 0 to $\varphi\bar{y}$. Now we introduce DT technology into yield distribution, i.e., condition yield distribution on DT as $F(y|DT)$ to reflect the distribution-wise effect of DT. Therefore, the effect of DT on actuarially fair premium $\bar{r}$ can be decomposed as

$$\frac{d\bar{r}}{dDT} = \varphi F(\varphi\bar{y}) \frac{\partial E(y|DT)}{\partial DT} + \int_0^{\varphi E(y|DT)} \frac{\partial F(y|DT)}{\partial DT} dy. \tag{12}$$

The positive first term reflects the DT effects through increasing mean yield (mean-increasing effect), and the second term represents the effects of shifting distribution while maintaining the same yield guarantee (risk-reducing effect). The status-quo yield distribution is first-order dominated by that under increasing DT, as seen in Fig. 3, hence the second term is negatively signed.

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Appendix

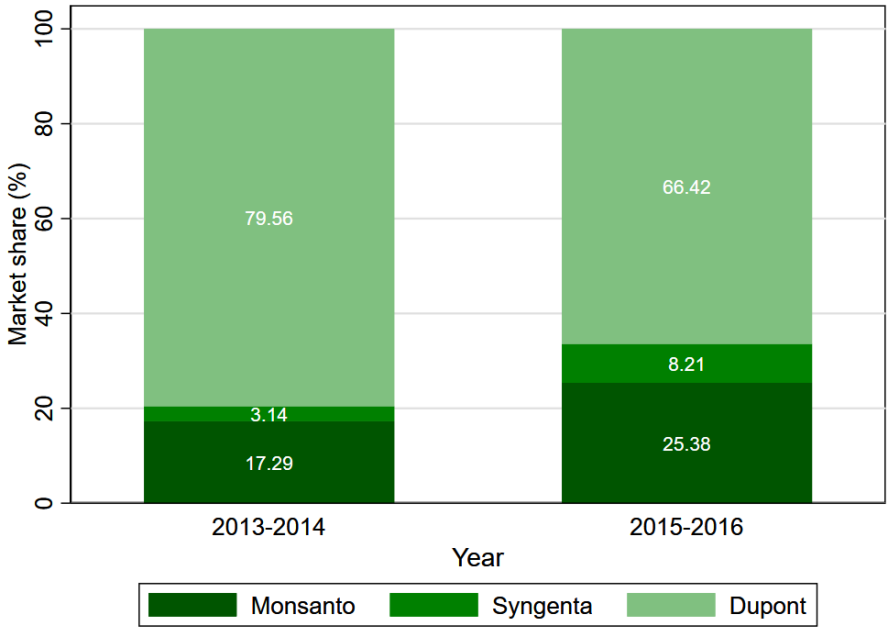


Fig. S1 Market shares (%) of top three companies providing drought-tolerant corn varieties, 2013-2016. Market share is measured as the company share of drought-tolerant corn acreage (two-year averaged). (Data source: TraitTrak®, Kynetec)

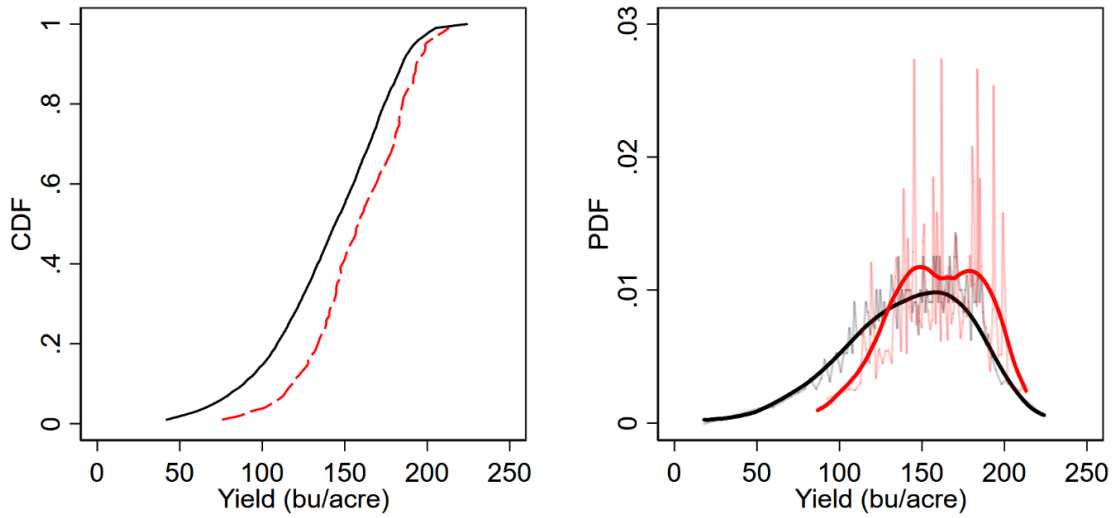


Fig. S2 Shifts in CDF (left) and PDF (right) under 20% increase in DT planting rate. The black lines are the empirical CDF and PDF in the sample, and the red lines are the estimates under a 20% increase in DT planting rate. PDF is approximated as $CDF(x_2)-CDF(x_1)/(x_2-x_1)$ where x_1 and x_2 are such that $CDF(x_2)-CDF(x_1)$ is 0.01. For example, at the median, x_2 is the yield at the 50^{th} quantile, and x_1 is the yield at the 49^{th} quantile. The approximations (the light black and red lines in the right panel) are then fitted using kernel density estimation to obtain smooth PDF functions for illustration purposes in the right panel.

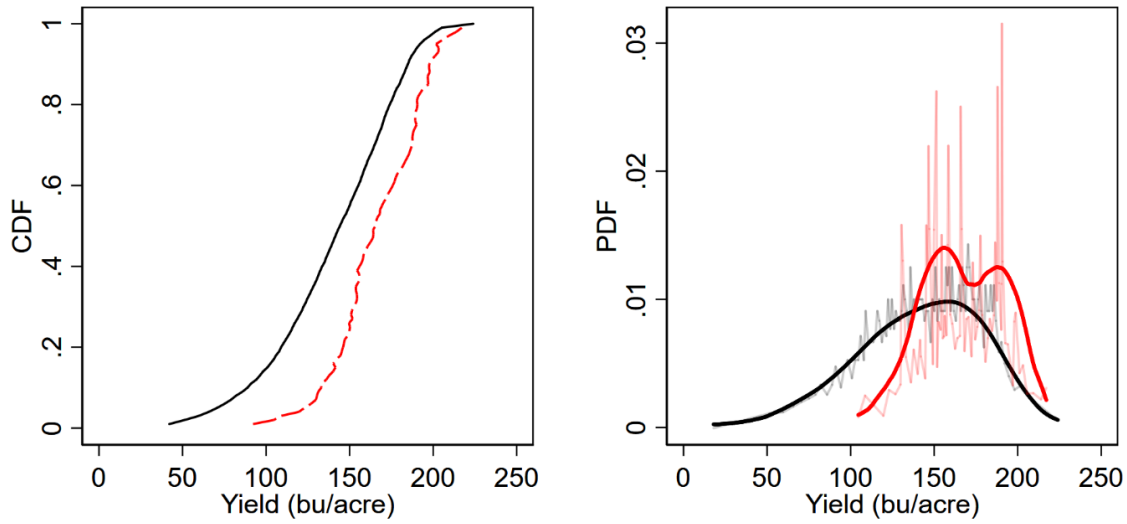


Fig. S3 Shifts in CDF (left) and PDF (right) under 30% increase in DT planting rate.

The black lines are the empirical CDF and PDF in the sample, and the red lines are the estimates under a 30% increase in DT planting rate. PDF is approximated as $CDF(x_2)-CDF(x_1)/(x_2-x_1)$ where x_1 and x_2 are such that $CDF(x_2)-CDF(x_1)$ is 0.01. For example, at the median, x_2 is the yield at the 50^{th} quantile, and x_1 is the yield at the 49^{th} quantile. The approximations (the light black and red lines in the right panel) are then fitted using kernel density estimation to obtain smooth PDF functions for illustration purposes in the right panel.

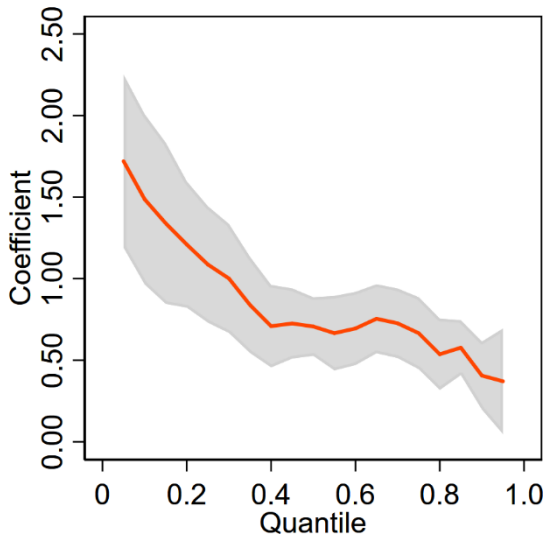


Fig. S4 Coefficient estimates of DT planting rate (%) variable with 1st GE stacking controlled, the 1st to 99th quantiles. The red line represents point estimates of quantile regression, and the shaded areas represent the 95% confidence interval. Standard errors are obtained by bootstrapping.

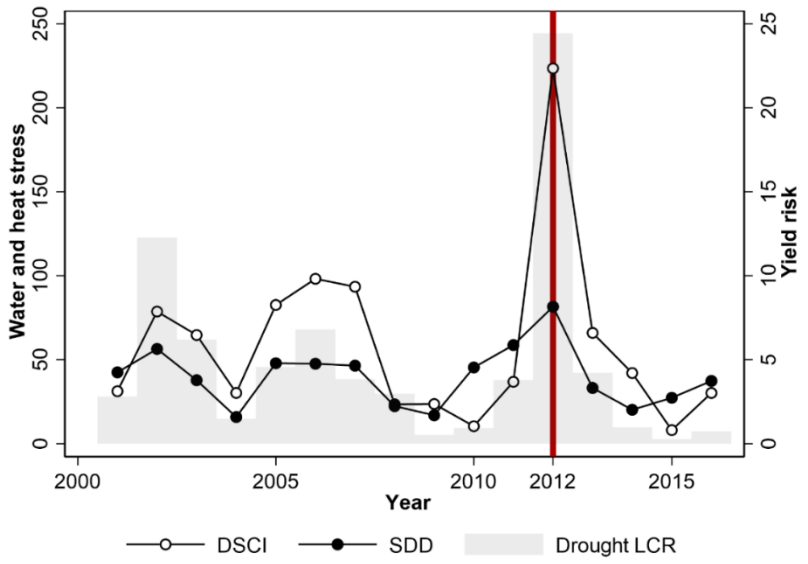


Fig. S5 Time trends of water stress, heat stress, and yield risk, 2001-2016. Water and heat stress is measured by the June-August average of Drought Severity and Coverage Index (DSCI) and April-September aggregated stress degree days (SDD), and yield risk is measured by the drought-related loss-cost ratio (Drought LCR, in %). (Date source: U.S. Drought Monitor; PRISM; and TraitTrak®, GfK Kynetec)

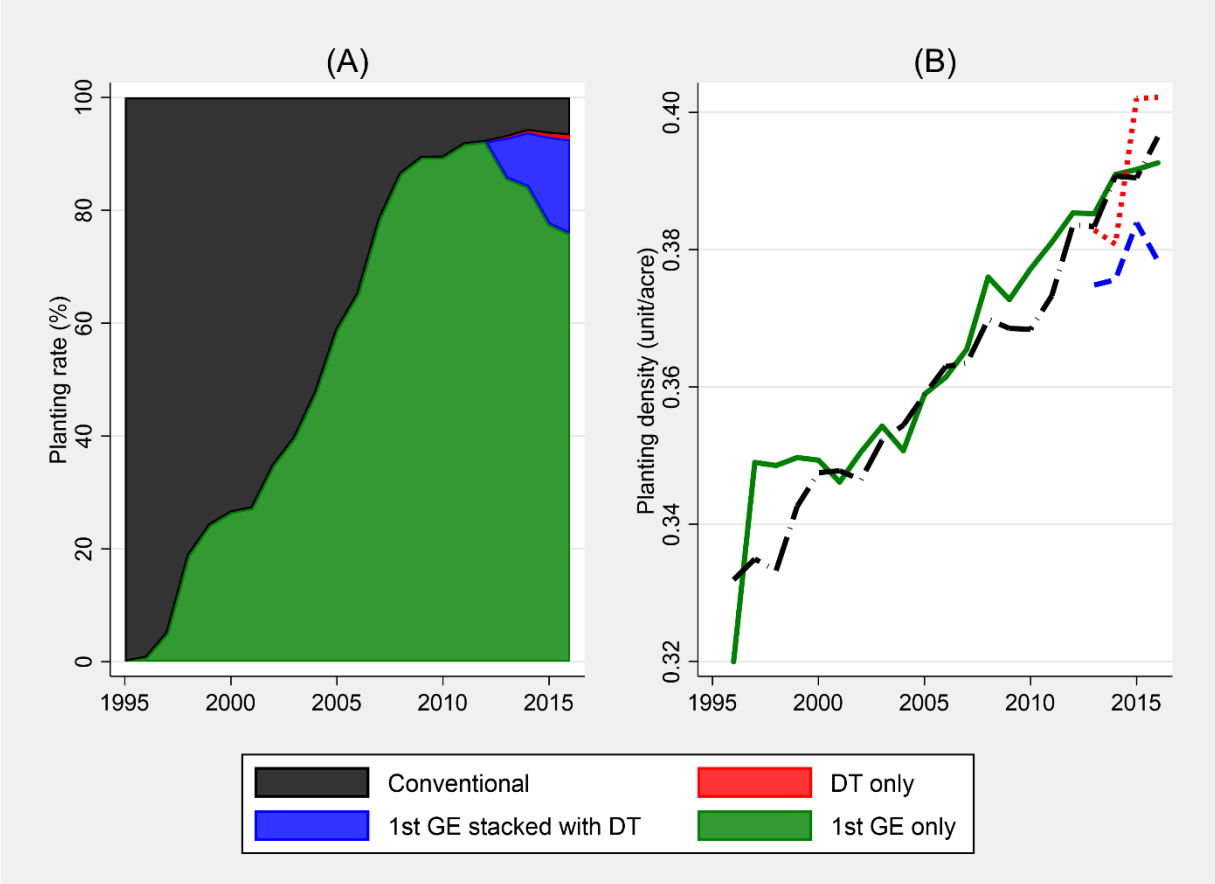


Fig. S6 Time trend of corn planting rate and density by seed varieties, 1995-2016. Panel: (A) Planting rate, measured as the percentage of corn acres (%) that plant respective variety. (B) Planting density, measured as the seed units per acre of corn planting. Seeds are classified into four categories: (1) DT only, containing only DT, namely no insect-resistant Bt or herbicide-resistant (HT) traits; (2) 1st GE only, namely first-generation GE that contains Bt or HT, but no DT embedded; (3) 1st GE stacked with DT, containing DT and 1st GE (Bt/HT); and (4) conventional seed, not containing Bt, HT, or DT. (Data source: TraitTrak®, Kynetec)

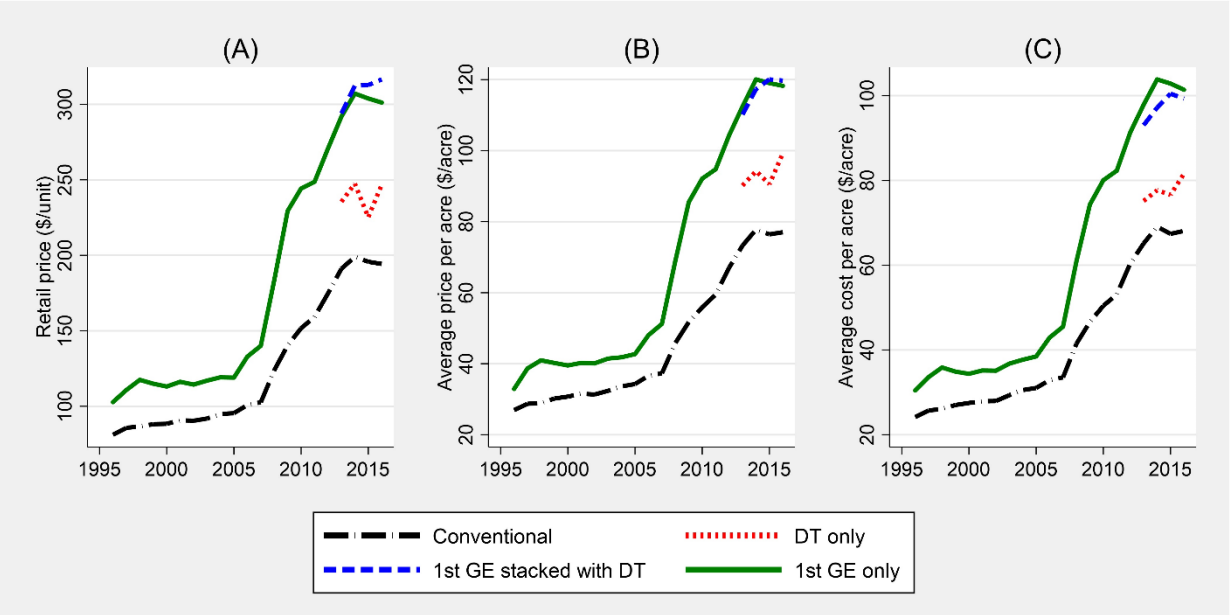


Fig. S7 Time trend of seed prices by seed varieties, 1996-2016. Panel: (A) Retail price ($/unit). (B) Average price per acre ($/acre). (C) Average seed cost per acre ($/acre), net of discounts, and free units. Seeds are classified into four categories: (1) DT only, containing only DT, namely no Bt or HT; (2) 1st GE only, namely first-generation GE that contains Bt or HT, but no DT embedded; (3) 1st GE stacked with DT, containing DT and 1st GE (Bt/HT); and (4) conventional seed, not containing Bt, HT, or DT. (Data source: TraitTrak®, Kynetec)