Exploring the Risk Management Benefits of Drought Tolerance Technologies: Insights from U.S. Corn Profitability

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Abstract

Increasing drought risk has prompted broad interest in farmers' use of crops with drought tolerance (DT) traits as a risk management tool, though little past research has explored these topics within the U.S. setting. This study uses nationally representative field-level data from the U.S. Department of Agriculture's 2016 and 2021 Agricultural Resource Management Surveys (ARMS) of U.S. producers to quantify the risk-related economic benefits of DT corn. We estimate theoretically grounded profit functions that allow DT adoption to influence both expected per-acre operating profit and its variance, while using a control function approach to address potential endogeneity in DT corn hybrid adoption decisions. A simulation-based expected utility framework is employed to calculate certainty equivalents under varying levels of risk aversion, focusing on the difference in certainty equivalents (ΔCE) between DT adoption and non-adoption scenarios. Measures of risk-adjusted net benefits are derived by comparing ΔCEs with DT seed premiums (roughly $5/ac), estimate from hedonic price regressions. We aggregate these benefits based on four groups defined by drought exposure and DT adoption status and simulate national benefits under counterfactual higher adoption rates. The results indicate that DT corn adoption provides minimal expected profit gains under non-drought conditions (up to a few dollars/ac) but meaningfully higher profits and certainty equivalents under drought stress. In 2021, aggregate risk-adjusted gains from DT were positive although modest. The counterfactual adoption simulations indicate that these gains would increase under higher DT adoption scenarios.

Keywords: Drought tolerance, risk management, profitability, control functions, seed premiums

JEL Codes: Q12, Q16, Q55

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1. Introduction

Rising climate variability—especially the increasing frequency and magnitude of drought and other heat-related stress—has heightened the urgency surrounding the development of agricultural innovations that bolster resilience (Ortiz-Bobea et al., 2021). One prominent response has been the introduction of drought-tolerant (DT) crop varieties designed to maintain yields under water stress. In the United States, DT corn hybrids (developed through both conventional breeding and genetic engineering) have emerged as a potential risk-mitigation tool for farmers. These varieties were first commercialized in 2011 and quickly gained traction in drought-prone regions, reflecting a demand for technologies that stabilize production risk (McFadden et al., 2019). While DT traits are also championed in developing countries to improve food security under erratic rainfall (Fisher et al., 2015), our focus is on the U.S. context, where managing downside yield risk and profit volatility has become increasingly important.

This paper investigates the role of the DT trait on two key moments of the distribution of per-acre corn profitability—both the mean and variance—under both drought and non-drought conditions. In estimating rigorous profit functions, we leverage insights about the nature of the drought-tolerance trait, its potentially heterogeneous efficacy across various environmental conditions, and its linkages to other important parameters of the corn production setting like irrigation access. We control for other G.E. traits, including herbicide tolerance (HT) and insect resistance (*Bacillus thuringiensis*, Bt), as well as crop insurance and field experience, to influence profit stability. Drawing on those results, we explore the potential for drought tolerance to reduce downside profitability risk, conceptualized as an increase in the certainty equivalent, under varying drought conditions and risk aversion. The extent to which such benefits meet or exceed prevailing DT seed premiums has implications for expected future adoption and thus future profitability under increasingly variable climate conditions. Counterfactual simulations consider the aggregate impacts of increased adoption relative to current levels. The discussion throughout the paper provides policy-relevant information on farmers' risk management through the avenue of technology adoption and its joint use with other risk-influencing inputs.

By 2016, about 22% of U.S. corn acres were planted to DT hybrids, and adoption since grew, though at a more modest pace, to 26% in 2021. Use has been far from uniform across regions: DT corn use is highest in the western Corn Belt and Great Plains, such as Nebraska and Kansas, where over one-third of both states' corn acreage was drought-tolerant in 2016. Adoption has been lower in the more humid Eastern Corn Belt and Southern states (Figure 1). This pattern is consistent with the notion of drought tolerance as a risk-management input. Farmers are disproportionately planting DT hybrids on more drought-prone fields and are less inclined to use them in areas where soil moisture stress tends to be severe and recurrent (McFadden et al., 2019). Such geography and management correlations underscore that growers perceive the value of DT corn primarily in reducing exposure to drought-induced losses.

Drought tolerance has begun to be a major objective of crop improvement efforts worldwide, backed by substantial public and private research and development (R&D) investments. In the U.S., seed companies have increasingly bundled DT traits into commercial corn seed portfolios, while emerging biotechnologies (including transgenic and gene-edited traits) are being leveraged to enhance crop drought resilience. Internationally, major initiatives have also promoted DT varieties to safeguard yields in climate-vulnerable regions. For instance, the Drought Tolerant Maize for Africa (DTMA) project released over 160 DT varieties across 13 countries between 2007 and 2013. These varieties demonstrated yield advantages under drought conditions in trial settings, though the adoption of DT hybrids abroad has been uneven. Barriers such as limited seed availability, high seed prices, and insufficient information about the technology's benefits have constrained wider adoption in several developing regions (Fisher et al., 2015). This global experience underscores that while DT crops hold promise for increasing agricultural resilience, realizing their potential may involve favorable market conditions that enable farmers to access and gain more familiarity with them.

Although the empirical determinants of U.S. farmers' DT corn adoption have been studied (McFadden et al., 2018, 2019, 2024), less is known about the economic effects of these varieties and their implications for risk management. Most research to date has focused on the agronomic performance of DT traits or on the determinants of adoption, rather than on outcomes like profitability and income risk. A major challenge in evaluating the value of the DT trait is the state-contingent nature of its benefits. The yield advantage of a DT hybrid manifests only in drought-stressed seasons, so a farmer does not observe what would have happened on the same field with a non-DT variety under those conditions. This lack of an observable counterfactual in any given year complicates both farmers' learning about the technology's effectiveness and analysts' efforts to measure its impact (e.g., Lybbert and Bell, 2010). In light of this uncertainty, important questions remain about how DT corn influences the distribution of farm profits and downside risk. These knowledge gaps motivate a closer examination of whether and how DT traits contribute to risk management and improve the economic resilience of U.S. corn producers.

Our study contributes to this literature by using nationally representative, field-level data from the United States to examine how DT traits impact profitability, input use, and risk exposure. Our study is related to a vein of the recent literature drawing that focuses chiefly on productivity effects, including related work in a forthcoming companion article (McFadden et al., 2025). Using yield trial data, Lee et al. (2024) found no yield advantage for DT seeds under average weather conditions but small positive effects from the DT trait in the western U.S. We explore the potential role of DT traits in risk mitigation, examining the effects on the distribution of farmers' operating profits under different agronomic and environmental conditions. Unlike past work that uses yield trial data under controlled settings, our work

leverages nationally representative field-level data from two waves of USDA's Agricultural Resource Management Survey (ARMS) in years 2016 and 2021.

The balance of this paper is as follows. We first describe the drought tolerant trait and briefly summarize past evidence of its effects on productivity, risk, and investment. We then present an empirical profit function framework that incorporates DT variety adoption. In this section, we also outline our methods for calculating net benefits that take into account potential risk reduction, while the next section overviews the data. Next, we present our estimates of field-level profitability effects and risk-related simulations, with major focus on the role of water-limited conditions as proxied by various measures of drought. A brief synthesis of the results and their associated policy implications are contained in the conclusion.

2. Background

Corn's tolerance to drought and other abiotic stresses has gradually improved over the past century, with some evidence suggesting that drought hardiness was a key driver in the early adoption of hybrid corn (Griliches, 1957; Sutch, 2011). Breeding progress since then has consistently raised yields in both optimal and water-stressed conditions (e.g., Duvick, 2005; Campos et al., 2006). Much of this resilience, however, has come about indirectly: breeders selected hybrids that thrive at higher planting densities, which also handle drought better (Fischer et al., 2014). Moreover, modern transgenic traits have provided additional drought resilience. For instance, corn with rootworm-resistant Bt genes suffer less damage and develop healthier roots, making the crop less vulnerable to drought stress (e.g., Marra et al., 2012). Yu and Babcock (2010) found U.S. corn has become more drought-tolerant since the 1980s, an effect partly attributed to Bt adoption; parallel gains in soybean (which has no Bt trait) underscore the important role of conventional breeding in improving stress tolerance. Additional studies suggest that today's corn yields are less sensitive to drought than in past decades, though the cost of drought relative to good weather has increased (Kuwayama et al., 2019; Lobell et al., 2020).

Focused efforts to develop explicitly drought-tolerant corn hybrids in the United States date back to at least the 1950s (Cooper et al., 2014), and by the 2010s, seed companies had introduced several DT products. Among those with the greatest market share are DuPont Pioneer's Optimum AQUAmax and Syngenta's Agrisure Artesian (both developed through conventional breeding) and Bayer's DroughtGard (a G.E. trait). As of its release, DroughtGard was the only transgenic drought trait on the market, incorporating a gene from *Bacillus subtilis* (a soil bacterium) that helps the corn plant maintain normal cellular function during water stress, thereby reducing yield loss under drought conditions (e.g., Nemali et al., 2015). By contrast, the AQUAmax and Artesian hybrids were created by screening vast breeding libraries for native drought tolerance genes and then using marker-assisted breeding (e.g., Messina et al.,

2023). Field studies indicate that both the G.E. and non-G.E. DT hybrids achieve water savings primarily by reducing early-season transpiration and use soil moisture more efficiently, helping to conserve water during crucial growth stages. Notably, these DT traits are designed to protect yields during moderate droughts and confer limited to no benefits under severe drought stress (McFadden et al., 2019).

In recent years, breeders have also turned to more precise gene-editing technologies to create new DT corn varieties. As one example, researchers at Corteva have used CRISPR/Cas9 to enhance the expression of a native drought-responsive protein, *ARGOS8*. This protein is a regulator of a specific hormone response that, among other effects, can slow corn development under drought stress. Instead of inserting a foreign gene, the scientists used CRISPR to make a genetic edit that boosts the plant's production of the *ARGOS8* protein. In field trials, the gene-edited variant yielded about five bu/ac more grain than the control hybrid under drought stress at the flowering stage of corn growth, with no significant yield penalty under optimal conditions, though there were no significant differences in yield at other stages of growth (Shi et al., 2017).

A growing body of research has evaluated the performance of DT corn using both experimental trials and farm-level data, in the U.S. and abroad. Evidence from U.S. field trials shows that DT hybrids tend to yield more than conventional hybrids under drought conditions but offer little or no advantage under well-watered conditions (Adee et al., 2016). Parallel results have also emerged from sub-Saharan Africa and other low-income regions, where conventional breeding programs have released drought-tolerant varieties (e.g., the DTMA project). These varieties likewise show yield gains in drought conditions, though with effects that vary by region, agricultural production system, stress timing (Wossen et al., 2017; Setimela et al., 2018; Paul, 2021; Boucher et al., 2024).

Because crop management decisions are interconnected, the adoption of DT corn may influence (and be influenced by) other management choices such as irrigation, tillage, and fertilizer applications. For example, farmers in rainfed systems may find DT hybrids sufficiently attractive that they substitute drought tolerance for investments in irrigation infrastructure. U.S. Department of Agriculture (USDA) survey data show that farmers with drought-prone soils are relatively more likely to plant DT corn, whereas those in irrigated areas have slightly lower adoption rates (Figure 1). On the other hand, DT corn adopters are more likely to also use conservation tillage and crop insurance, perhaps suggesting that they form a complementary risk-mitigation bundle of practices (McFadden et al., 2019). Thus, while DT corn mainly provides an immediate protective effect, it is interconnected with other risk management decisions in its effects on profitability, a stylized fact that helps to inform our model specification detailed below.

3. Empirical Approach

To identify the risk management implications of the DT trait related to farmers' financial outcomes, we develop a three-part empirical strategy: 1) identification of well-defined, theoretically consistent profit functions, 2) estimation of predicted profits and certainty equivalents across combinations of DT corn adoption and moderate drought, and 3) calculation of risk-adjusted net benefits per acre and in aggregate. Although a more unified framework could be developed to jointly produce all results, we follow a hybrid approach that combines structural profit function estimation and reduced-form regressions for empirical tractability.

3.1 Profit Function Estimation

To isolate the average effects of the DT trait on U.S. corn profitability, we first estimate operating profit as a function of drought tolerant status, prices of other productive inputs, quasi-fixed factors, interactions between prices and factors, and other exogenous variables that control for year, state, soil structure, weather deviations, and farm structure. Because the exact nature of the profit function is unknown, we estimate two widely applied specifications: a Cobb-Douglas function and a translog function. For any given corn field, the restricted, normalized translog profit function has the form:

$$\ln(\pi) = \beta_0 + \sum_i^M \beta_i \ln(P_i) + \frac{1}{2}\sum_{i=1}^M \sum_{j=1}^M \gamma_{ij} \ln(P_i) \ln(P_j) + \sum_{i=1}^M \sum_{k=1}^N \alpha_{ik} \ln(P_i) \ln(Z_k) + \sum_{k=1}^N \delta_k \ln(Z_k) + \frac{1}{2}\sum_{k=1}^N \sum_{l=1}^N \lambda_{kl} \ln(Z_k) \ln(Z_l) + \varepsilon, \quad (1)$$

where π is operating profit, P are normalized prices corresponding to the M set of productive inputs, Z is the set of N quasi-fixed factors, and ε is the econometric error term. If the interaction, cross-term, and quasi-fixed factor effects $(\gamma_{ij}, \alpha_{ik}, \delta_k, \lambda_{kl})$ are all zero, then the translog specification reduces to the conventional Cobb-Douglas function.

For both the translog and Cobb-Douglas profit functions, we parameterize the variance as a function of DT seed use, the other quasi-fixed factors, and a set of risk-related controls. For field n, we assume heteroskedasticity such that the error term, $\varepsilon_n \sim N(0, \sigma_n^2)$, has variance of the form:

$$\ln(\sigma_n^2) = \theta_0 + \sum_i^O \theta_i \ln W_{in}, \quad (2)$$

where $\boldsymbol{W}$ is the set of regressors that would be expected to have significant bearing on the underlying variance of per-acre profits. The most general version of this model assumes that the set of variables influencing the mean also influences the variance (i.e., $[\boldsymbol{P}, \boldsymbol{Z}] = \boldsymbol{W}$ with $N + M = O$). However, the dimensionality of the data, complexity of the maximum likelihood estimator, and collinearity can result in

poor performance under $[\boldsymbol{P}, \boldsymbol{Z}] = \boldsymbol{W}$. To aid estimation, we impose the restriction that the coefficients on all components of $\boldsymbol{W}$ other than the quasi-fixed factors and certain other relevant inputs are zero.[1]

Though a wide array of productive inputs influence the costs and revenues of corn production, among the most important factors for variable production costs include seeds, agri-chemicals, and energy use. Recent national cost-of-production data for the U.S. indicate that these three inputs, collectively, comprise more than 70% of corn producers' operating costs per acre (Saavoss et al., 2021).[2] We incorporate these by including unit input prices for seeds, fertilizer, and diesel, denoted below as $S, F,$ and W, respectively.

The quasi-fixed factors are inputs that are time-predetermined or not easily adjustable in the production process, such as land or indivisible capital equipment that is not able to be easily acquired or repurposed for corn production. From among the potentially large number of plausibly fixed factors that influence profitability, we choose those that have been noted in the literatures on U.S. corn production and productivity to 1) have significant effects on profitability, and 2) are measured rigorously over time (e.g., Gillespie et al., 2025). Besides the main variable of interest, DT seed use (D), we also include irrigation access (I), years of field-level experience as a proxy for human capital (E), and capital recovery per machine (C).

We specialize equations (1) and (2) to our setting and normalize the profit function by dividing the dollar-valued inputs by the real corn price to impose homogeneity. However, operating profit, which is the gross value of corn production less variable costs, can be negative for producers experiencing low commodity prices, poor yields, high input costs, or other adverse shocks. To avoid discarding these observations, we apply the inverse hyperbolic sine (IHS) transformation to the per-acre profit measure. This transformation behaves similarly to a logarithm transformation while permitting zero and negative values to be retained (e.g., Bellemare and Wichman, 2020). Denoting normalized prices and factors with asterisks[3], this results in the following translog specification for field n:

$$\begin{aligned}\operatorname{arcsinh}(\pi_n) = {} & \beta_0 + \beta_S \ln(P_S^*) + \beta_F \ln(P_F^*) + \beta_W \ln(P_W^*) + 0.5\gamma_{SS} \ln(P_S^*)\ln(P_S^*) + \\ & 0.5\gamma_{FF} \ln(P_F^*)\ln(P_F^*) + 0.5\gamma_{WW} \ln(P_W^*)\ln(P_W^*) + 0.5\gamma_{\mathrm{SF}} \ln(P_S^*)\ln(P_F^*) + 0.5\gamma_{SW} \ln(P_S^*)\ln(P_W^*) + \\ & 0.5\gamma_{FW} \ln(P_F^*)\ln(P_W^*) + \delta_{\mathrm{D}} D_n + \delta_{\mathrm{I}} I_n + \delta_{\mathrm{E}} \ln(E_n) + \delta_{\mathrm{C}} \ln(C_n) + \lambda_{\mathrm{DD}} D_n D_n + \lambda_{\mathrm{II}} I_n I_n + \\ & \lambda_{\mathrm{EE}} \ln(E_n)\ln(E_n) + \lambda_{\mathrm{CC}} \ln(C_n)\ln(C_n) + \alpha_{SD} \ln(P_S^*)\ln(S_D) + \alpha_{SI} \ln(P_S^*)\ln(I_n) +\end{aligned}$$

[1] In estimation, $\boldsymbol{Z}$ typically contains a number of control variables, including time and geographic fixed effects, thus there can be situations in which these controls and fixed effects do not necessarily need to be included in $\mathbf{W}$.

[2] Chemicals (e.g., pesticides, fungicides, insecticides, nematicides) are another significant corn production expense. However, deriving chemical input prices is challenging because units of active ingredients are incommensurate across products, necessitating the use of quality-adjustment procedures (e.g., Fernandez-Cornejo and Jans, 1995; Shi et al., 2010). Inclusion of unadjusted chemical prices in the regression specifications does not qualitatively change the regression results presented below. We leave for future profitability research regression specifications that include quality-adjusted chemical prices.

[3] To reduce notational burden, subscripts denoting field n for each of the input prices has been suppressed.

$$\alpha_{SE}\ln(P_S^*)\ln(E_n) + \alpha_{SC}\ln(P_S^*)\ln(C_n) + \alpha_{FD}\ln(P_F^*)\ln(S_D) + \alpha_{FI}\ln(P_F^*)\ln(I_n) + \alpha_{FE}\ln(P_F^*)\ln(E_n) + \alpha_{FC}\ln(P_F^*)\ln(C_n) + \alpha_{WD}\ln(P_W^*)\ln(S_D) + \alpha_{WI}\ln(P_W^*)\ln(I_n) + \alpha_{WE}\ln(P_W^*)\ln(E_n) + \alpha_{WC}\ln(P_W^*)\ln(C_n) + \boldsymbol{X_n}\boldsymbol{\phi} + \varepsilon_n, \quad (3)$$

with the log-variance equation being:

$$\ln(\sigma_n^2) = \theta_0 + \theta_D D_n + \theta_I I_n + \theta_E \ln(E_n) + \theta_C \ln(C_n) + \boldsymbol{W_n}\theta. \quad (4)$$

In specifications (3) and (4), $\boldsymbol{X_n}$ is a vector of control variables influencing the mean of per-acre operating profit, and $\boldsymbol{W_n}$ is a vector of controls the affect the variance. As explained further in the data section, both of these vectors include measures of drought incidence and severity, in addition to other field- and farm-level characteristics deemed to be relevant.

Unobserved heterogeneity in operator managerial ability or land quality, among potentially other factors could be correlated with farmers' DT seed use. For instance, highly-skilled farm operators with exceptional knowledge of their production systems could be inclined to adopt (or not adopt) DT seeds based on their expectations of varietal performance and ease of integration into their system. If this expertise is not sufficiently captured in our control variables and is correlated with DT seed adoption and production outcomes, the estimated coefficient on DT seed adoption, as well as interaction terms involving DT seed adoption, could be biased. Roughly similar arguments could be made with perceived land quality or expected pest infestations. To help mitigate potential bias, we make use of a common two-stage residual inclusion (2SRI) method: control functions (e.g., Terza et al., 2008; Wooldridge, 2015). These methods are becoming increasingly prevalent in the literature on the impacts of discrete technologies, such as studies on the yield and damage-abatement effects of GE traits (e.g. Wechsler and Smith, 2018) and precision agriculture (e.g. McFadden et al., 2022), for instance. In the first stage, we estimate probit regressions of DT seed use that condition on all exogenous variables in the model, including year and state fixed effects, soil structure and topography, weather deviations from climate normals, and farm structure and demographic controls. From these regressions, we calculate the generalized residuals as the score of the log-likelihood.[4] Because DT-related interaction terms are formed with certain continuous variables (explained below), calculation of generalized residuals for those involve use of ordinary least squares regressions.

Though identification is technically achieved due to nonlinearity, we reinforce our approach through employment of an excluded instrument: continuous DT seed use. In particular, we make use of

[4] For observation n, Wooldridge (2015) notes the generalized residual is calculated as $D_n \cdot m(\boldsymbol{z_n}\hat{\alpha}) - (1 - D_n) \cdot m(-\boldsymbol{z_n}\hat{\alpha})$, where $m(\cdot) = \phi(\cdot)/\Phi(\cdot)$ is the inverse Mills ratio, $\boldsymbol{z_n}$ is a vector of exogenous covariates explaining DT seed use, and $\hat{\alpha}$ are the estimated coefficients from the first-stage probit regression, $D = \boldsymbol{z\alpha} + \boldsymbol{\mu}$.

information on whether the farmer used a DT-traited corn seed in the previous season. This instrument is expected to satisfy the exclusion restriction in that "hold-over effects" between seasons do not exist, to our knowledge. In other words, we are not aware of compelling agronomic reasons why planting DT-traited corn in the last corn rotation would have an impact on corn production in the current season.[5] Moreover, we expect continuous DT seed use to be a strong instrument because there are natural incentives for farmers to plant DT seed use across multiple corn seasons so as to better learn about the seeds' efficacy. As Lybbert and Bell (2010) suggests, multiple growing seasons can be needed for farmers to disentangle the effect of the DT trait in the face of variable weather shocks that can occur throughout the growing season.

Since a major focus is on the performance of DT seeds under water-limited conditions, we examine to what extent the impact of various drought conditions on profitability can be mitigated by the DT trait. Indeed, seed manufacturers have consistently claimed that the DT trait can improve yields under water-limited conditions but are likely to be of limited help in the face of severe-or-worse drought (e.g. Lybbert and Carter, 2015). As such, in the analysis that follows, much of our concern centers on DT-related interaction terms rather than main-level DT effects. The severity and timing of drought play a critical role, which drives our interest in using measures like average and maximal values of the Palmer Modified Drought Index (PMDI) and indicators of U.S. Drought Monitor categories (e.g., D1 or "moderate drought"), as detailed more below.

Substituting in equation (4), equation (3) is estimated using standard maximum likelihood techniques. Given the two-stage nature of the profit function estimations, we bootstrap the standard errors with $B = 2{,}000$ bootstrap samples that have been re-sampled with replacement according to the survey's base weight (expansion factor). Similarly, due to the size of the specification and sample, we test for monotonicity post estimation at the sample means instead of attempting to impose it at each observation in the data.[6]

3.2 Certainty Equivalents and Risk-Adjusted Net Benefits

Assessing the impacts of technologies like drought-tolerance traits on expected U.S. corn profitability and its variance—while valuable in and of itself given the scant literature on DT effects in developed

[5] Although the DT trait tends to be stacked with herbicide tolerance and/or insect resistance, it is not expected that DT-induced reductions in vulnerability to pest population levels in the previous season (if any) would have an impact on growing conditions in the current season. The same is expected to be true with any DT-induced water "savings" from the previous season in which DT corn was grown. Given that DT corn is not more or less likely to be in a corn-soybeans or corn-corn rotation (McFadden et al., 2019), any minor DT based change in soil moisture or weed seed banks, for example, would be expected to be "used up" before the next season.

[6] We find that monotonicity with respect to each of the three input prices holds at the sample means, as well as for the vast majority of data points in the analysis sample.

countries—does not directly address risk. For instance, the net impact of technologies that have meager effects on mean profits but reduce profit variability may not be immediately apparent in some profitability analyses. As such, we expand our analysis to an expected utility framework that explicitly incorporates farmers' risk preferences to shed (e.g., Tack and Yu, 2021).

A technology like DT corn could reduce economic risk if it narrows the distribution of outcomes in a way that lowers the farmer's risk premium, in line with recent work that has found risk reductions on fields with G.E. corn (e.g., Goodwin and Piggott, 2020). In other words, by reducing downside exposure or stabilizing returns under adverse conditions, DT seeds could raise the certainty equivalent (π^{CE}) of production, i.e., the point at which $U(\pi^{CE}) = E[U(\tilde{\pi})]$, where $U(\cdot)$ is a concave utility function and $\tilde{\pi}$ is risky profit stream.[7] In aggregate, by increasing the "guaranteed" return that farmers would accept in exchange for the risky prospect inherent in annual corn production, we would expect improvements in farmers' aggregate financial well-being, other things equal (e.g., Moschini and Hennessy, 2001).

Towards a better understanding of the role that DT corn plays in risk management, we put forward a simple expected utility model and simulate changes in certainty equivalents as a way of uncovering the potential risk-adjusted net benefits of the technology. Specifically, we assume that farmers' expected utility can be characterized by a constant absolute risk aversion (CARA) utility function:

$$U(\tilde{\pi}) = 1 - \exp(\rho\tilde{\pi}), \tag{5}$$

where ρ is the coefficient of absolute risk aversion. Unlike the more common constant relative risk aversion (CRRA) utility function, defined on $(0, +\infty)$, CARA utility functions are defined for all real numbers. CARA utility is unrealistic in the sense that it implies farmers' risk tolerance is constant in dollar terms (e.g., losing $1 reduces utility by the same amount regardless of wealth levels). However, this functional form 1) is straightforward to apply directly to loss-riddled measures of U.S. corn profitability, 2) has been well studied in the related agricultural economics literature (e.g., Babcock et al., 1993), and 3) has been found to be a useful approximation of risk behavior in broader U.S. agriculture production settings (Just, 2011). Because our primary aim is to provide a first step towards identifying the risk-reducing potential of DT corn in a national setting, rather than derive an exhaustive set of fully robust estimates, say, for direct use in insurance or financial markets, this tradeoff between tractability and realism seems tolerable.[8]

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[7] Assume that (unconditional) expected profits per-acre for a field with DT corn is roughly equal to expected profits without DT corn, other things equal. A reduction in the risk premium ($E[\tilde{\pi}] - \pi^{CE}$) as a result of adopting DT corn implies an increase in the certainty equivalent: $E[\tilde{\pi}_{D=1}] - \pi^{CE}_{D=1} < E[\tilde{\pi}_{D=0}] - \pi^{CE}_{D=0} \Rightarrow \pi^{CE}_{D=1} > \pi^{CE}_{D=0}$.

[8] Forthcoming companion research explored reduced-form models of profitability using similar Agricultural Resource Management Survey (ARMS) data, though the emphasis was on uncovering DT effects on average yields

Substituting equation (5) into the definition of π^{CE} results in the well-known expression for the CARA utility certainty equivalent, $\pi^{CE} = -\frac{1}{\rho}\ln(1 - E[U(\pi)])$. One intuitive measure of the risk-adjusted returns to the technology is thus the difference in certainty equivalents between adoption and nonadoption, $\left[\pi^{CE}_{D=1} - \pi^{CE}_{D=0}\right]$. We would expect this differential to be positive and perhaps increasing in various measures of drought incidence (e.g., severity, duration, frequency). When evaluating the effectiveness of DT corn for profit stabilization, the farmer should weigh the (per-acre) incremental benefit from adoption with the technology's incremental cost, which can be viewed as the per-acre premium for the drought tolerance trait, $Prem_{DT}$. The extent to which the CE difference exceeds the DT trait premium can be thought of as a risk-adjusted net benefit:

$$NB = -\frac{1}{\rho}\left[\ln\left(1 - \overline{U(\pi)}_{DT=1}\right) - \ln\left(1 - \overline{U(\pi)}_{DT=0}\right)\right] - Prem_{DT}, \tag{6}$$

with $\overline{U(\pi)} \equiv E(\pi)$. To simulate this net benefit function for each field, we first generate predicted profits using estimates from Cobb-Douglas versions of equations (3) and (4) under scenarios of full adoption and nonadoption.[9] We then simulate profit draws for both scenarios by back-transforming from the inverse hyperbolic sine and introducing variability based on the variance terms estimated in equation (4):

$$\tilde{\pi}_{DT=1} = \sinh(\hat{\pi}_{DT=1} + \hat{\sigma}^2_{DT=1} \cdot \nu_{DT=1}) \tag{7}$$
$$\tilde{\pi}_{DT=0} = \sinh(\hat{\pi}_{DT=0} + \hat{\sigma}^2_{DT=0} \cdot \nu_{DT=0}). \tag{7'}$$

In these equations, $(\tilde{\pi}_{DT=1}, \tilde{\pi}_{DT=0})$ are profit draws under the DT adoption and nonadoption scenarios, $(\hat{\pi}_{DT=1}, \hat{\pi}_{DT=0})$ are predicted profits, $(\hat{\sigma}^2_{DT=1}, \hat{\sigma}^2_{DT=0})$ are estimated variances, and $\nu \sim N(0_2, I_2)$. Next, we assume $\rho \in \{0.005, 0.01, 0.02\}$, which is within the range considered in past studies, though on the somewhat higher end. Certainty equivalent differences are calculated based on averaging utility across the 1,000 draws.

Past work has shown that the effects of the DT technology on corn yields varies by drought conditions, as expected (e.g., Adee et al., 2016; Lee et al., 2024; McFadden et al., 2025, forthcoming). To explore possible heterogeneity by drought status, we refine the procedure by producing simulations across four combinations of DT adoption and drought, with drought being defined as incident of moderate drought conditions based on average values of the PMDI (see data section below). The four combinations are $(DT, Drought) = (0,0), (0,1), (1,0), (1,1)$.

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and yield variability. Those results suggested little effect on average profitability of using DT corn (McFadden et al., 2025, forthcoming).

[9] The Cobb-Douglas specifications were chosen over the translog specifications for reasons of 1) faster convergence, leading to quick simulation times, and 2) to avoid any potential bias in predicted values arising from collinearity among the several square and cross-product terms in the translog specification.

To generate the DT trait premiums necessary for calculating the risk-adjusted net benefit expression in equation (6), we estimate hedonic price regressions using similar seed prices available in our data.[10] Hedonic regressions have been widely used to construct quality-adjusted price indices and to value new product innovations. Fernandez-Cornejo and Jans (1995) used a hedonic framework to derive quality-adjusted price indices for pesticides, while Shi et al. (2010) and Ciliberto et al. (2019) have used similar framework to derive G.E. seed trait premiums. In our analysis, we regress per-acre, seed prices (expressed in 2021 dollars) on an indicator of the DT trait, an indicator for herbicide tolerance (HT) or insect resistance (Bt) traits, and an array of state fixed effects. In robustness checks, we add additional regressors meant to proxy for local seed market effects, farmers' experience purchasing seeds, and other relevant factors. By controlling for state, the DT trait coefficient is identified from within-state price variation, ensuring that, for example, the measured trait premium is not confounded by regional price differences correlated with where DT hybrids are grown. See Table A2 in the Appendix.

To generate estimates of the aggregate net benefits, we scale up the per-acre effects found using equations (5), (6), and (7) to the national level using information about the 2021 corn acreage across the four $(DT, Drought)$ combinations. We also explore three counterfactual scenarios in which 2021 DT acreage across the was 5%, 10%, or 20% higher than its realized level. We assume that total 2021 corn acreage remains unchanged; thus, increased DT corn adoption necessarily reduces non-DT acreage. However, for simplicity, we assume that the share of DT acreage under drought and non-drought conditions, and similarly the share of non-DT acreage under drought and non-drought conditions, remains unchanged across the scenarios.[11]

4. Data and Descriptive Statistics

Responses to the 2016 and 2021 waves of the Agricultural Resource Management Survey (ARMS) make up our primary dataset. ARMS is a main source of information to the USDA about the production practices and financial well-being of U.S. farms, designed to characterize fields, farms, and farm households that are representative at the state and national level. ARMS Phase 2 is a detailed field-level survey that, for each sampled respondent, inquires about farm production practices (e.g., conservation

[10] The theoretical foundation for hedonic pricing was formalized by Rosen (1974), who modeled product differentiation under competitive equilibrium. Rosen showed that in a market of heterogeneous goods, an equilibrium "hedonic price function" emerges relating a product's price to its characteristics. The slope of this function with respect to any attribute gives the implicit marginal price of that attribute, reflecting both consumers' marginal willingness-to-pay and producers' marginal cost for the attribute in equilibrium. Assuming markets are competitive, a regression of observed prices on product traits provides unbiased estimates of the traits' implicit values.

[11] In 2021, the share of DT corn acreage in which a moderate drought occurred at some point during the growing season (April-September) was 28.3%, while the share of non-DT corn acreage in which a moderate drought occurred was 43.0%. It would be straightforward to simulate changes in the distribution of drought realization, which we leave for future work.

practices, chemical and fertilizer applications), labor, and capital used to produce the surveyed crop on a randomly selected field. Major field crops (e.g., corn, cotton, soybeans, wheat) and livestock commodities are surveyed on rotating basis every 4-10 years. ARMS Phase 3 is a farm-level survey that primarily asks about the economics of the farm operation, in addition to demographics and other characteristics of the farm household. Unlike ARMS Phase 2, which is distributed only to farms growing the target commodity in areas with major acreage of this commodity, ARMS Phase 3 is sent to operators of farms of all production specializations and sizes throughout the conterminous U.S. Many of our main variables (DT seed use, irrigation access, years of field experience, crop insurance uptake, and others), are directly from ARMS Phase 2, while the profitability and the price-related variables are derived from these questions.

We construct a binary indicator for drought-tolerant (DT) seed use from an ARMS Phase 2 survey question asking whether the corn planted on the field had a drought-resistance/tolerance trait. This question appears in the survey section on G.E. traits, but evidence suggests farmers interpret it broadly to mean any drought-tolerant variety, not solely a GE trait (McFadden et al., 2019). In addition to this current-year indicator, we construct a measure of continuous DT seed use to capture adoption in consecutive years. The 2016 ARMS asked if the farmer grew DT corn on that field in the previous year, and we use that response to indicate ongoing DT use. The 2021 survey posed a similar question ("…the last time corn was planted on the field"); we convert those responses to a "last-year basis" by confirming whether corn was planted on the field in the prior year.[12]

Per-acre operating profit for U.S. corn production is obtained from USDA-ERS's annual Commodity Costs and Returns (CAR) data (USDA-ERS, 2025). Operating profit is defined as the gross value of corn production (including both grain and silage) minus total operating costs. These operating costs are expenditures on seed, fertilizer, chemicals, custom services, electricity, fuel and lubrication, purchased irrigation water, repairs, and interest on operating capital. ERS employs distinct methodologies and data sources for many of these cost components, as detailed in Gillespie et al. (2025).

From the same ARMS-based CAR dataset, we extract several price measures and quasi-fixed factors, including seed prices (per 1,000 seeds), fertilizer prices (per pound), and diesel prices. These are constructed based on a direct costing approach that relies on information reported in other parts of the survey. Because gallons of fuel used are not inquired about or internally imputed by ERS, we use per-machine outlays as a proxy for the unit price.[13] Similarly, our measure of the unit price of capital, a quasi-fixed factor in our model, is capital recovery per distinct machine used in field operations, following

[12] This is done by examining responses to the previous crop planted using information from the crop history table of the survey.

[13] Future versions of this research will examine robustness to using regional diesel prices (e.g., EIA on-highway diesel prices) in place of our current constructed measure.

similar approaches relying on this variable (e.g., Key and McBride, 2014). To avoid the potential for induced collinearity from using per-acre land prices, we control land and farm size in the regressions by including corn enterprise size quartiles. County-level corn prices (aggregated from daily elevator prices) are taken from GeoGrain aggregated from daily elevator prices). We use the Producer Price Index (PPI) - All Commodities to express all financial variables in 2021 dollars.

The ARMS Phase 2 data provide many additional field-level variables needed for the analysis. To proxy for other risk-management choices, we include an indicator for whether the field's corn crop was covered by a federal crop insurance policy. In a related vein, irrigation access is also constructed as an indicator variable based on information collected in the irrigation section. To account for managerial expertise and the stock of human capital (as a quasi-fixed factor), we use the number of years the operator has farmed the field. An indicator for whether the seed planted had an HT or Bt trait, based on the survey's G.E. traits section, is also included. We control for a variety of field characteristics: the field's slope (five categories, from nearly flat to steep grade with variable slope), soil texture, and whether any portion of the field is designated as a wetland or classified by NRCS as highly erodible land.

We quantify drought stress—and its interaction with DT seed use—in three ways. First, we use the PMDI, a continuous metric of long-term drought conditions (NOAA-NCEI, 2025). For each field's county, we take the monthly PMDI values from April through September and calculate their average to represent overall growing-season drought severity. (Because the PMDI is negative during dry spells, we multiply it by –1 so that higher values in our data indicate more severe drought.) Second, we construct an alternative PMDI-based measure using the maximum (worst) PMDI value observed between April and September, to capture peak drought intensity. Third, we incorporate standard drought classification categories derived from the PMDI. Using the PMDI-based thresholds, we identify months that fall into abnormally dry (D0), moderate drought (D1), severe drought (D2), extreme drought (D3), or exceptional drought (D4) conditions.[14] From these, we create indicator variables signaling whether the field's county experienced any drought of a given severity during the April–September growing season (e.g. a dummy for whether a D1 drought occurred at any point in the season).

The impact of drought on yield can depend heavily on the crop's growth stage at the time of the stress (e.g., Adee et al., 2016). We therefore develop measures of drought occurrence aligned with specific corn development stages. Although ARMS records each field's planting date, it does not track dates of subsequent growth stages (e.g. silking or maturity). To estimate when each field likely reached key stages, we use two complementary approaches. First, we align field planting dates with weekly drought data and state-level crop progress reports. The U.S. Drought Monitor (USDM) provides weekly county-level

[14] The following standard classification is used: D0 for PMDI in (-2,-1], D1 for PMDI in (-3, -2], D2 for PMIDI in (-4, -3], D3 for PMDI in (-5, -4], and D4 for PMDI $\leq$ -5.

drought severity readings (in the same D0–D4 categories mentioned above). Further, NASS Crop Progress reports detail the percentage of corn acreage that has reached various stages (planted, emerged, silking, milking, dough, dented, mature, harvested) each week by state. Using the state-level crop progress data, we infer the typical time intervals between stages for each state. We then combine this with the known planting date of the field to approximate the calendar week in which that field would be at each growth stage. By merging these estimated stage timings with the weekly county USDM data, we can identify the drought severity category (if any) affecting the field during each stage of development. In our analysis we pay particular attention to drought during the silking stage, as prior research suggests silking is the most critical stage for yield loss mitigation by the DT trait (e.g., Paul, 2021).

The crop progress-based method above relies on state averages, which may not fully capture within-state variation in crop development due to localized weather. Therefore, we also implement a second method to predict growth stages using growing degree days (GDDs) (Eckert and Thomison, 2017). This approach uses daily temperature data to simulate crop growth for each field. We use daily minimum and maximum temperatures at the county level (from PRISM) and compute cumulative GDDs starting from the planting date. We apply the standard "86/50" rule for corn, calculating $GDD = ((T_{max} + T_{min})/2) - 50$, where T_{max} is either the daily maximum temperature or 86 °F (whichever is lower) and T_{min} is the daily minimum temperature or 50 °F (whichever is higher). These daily GDDs are summed from planting onward to estimate the crop's progress through developmental milestones.[15] We then link those estimated stage dates to the weekly USDM data to determine the drought severity the field likely experienced at each growth stage. This yields an alternative set of stage-specific drought exposure variables (e.g., an indicator of drought severity during the silking period, among others).[16]

Figure 2 illustrates the county-level distribution of drought-tolerant (DT) corn fields in our dataset, highlighting broad geographic coverage across the major corn-producing regions surveyed in 2016 and 2021. As noted earlier, drought-prone areas of the western Corn Belt and Great Plains had the highest uptake rates of DT corn. In the 2021 survey wave, the core adoption region remained centered in water-stressed locations, though there was greater uptake in the southeast U.S. as the drought tolerance trait became embedded in hybrids more suitable (and more broadly marketed) to this part of the U.S.

Table 1 presents summary statistics and provides further insight into the sample's characteristics. The mean operating profit is roughly $407/ac (2021 dollars), with considerable variability—the 5th percentile is $16 while the 95th percentile reaches $784. On average, 24% of fields in our sample have

[15] While the exact GDD requirement for each stage can vary by hybrid maturity rating, prior work has shown planting date to be a more important determinant of realized timing than the hybrid's relative maturity (Baum et al., 2019).

[16] For space considerations, we do not report regression results using this second measure of stage-of-growth drought stress.

corn with the DT trait, though nearly 95% of fields are planted with corn varieties containing other gene G.E. traits. The fact that the DT trait tends to be stacked with at least one other G.E. trait again underscores the importance of controlling for relevant genetic characteristics. The average corn price was about $4.73/bu, and farmers paid roughly $3.49 per 1,000 seeds (on the order of $100 per acre at common planting densities), alongside moderate fertilizer prices (around $0.73/lb), and fuel prices. Roughly 87% of the fields were insured and were operated by farmers with 23 years of experience, tied to operations of moderate corn enterprise size (on average, 714 corn acres).

The data also shed light on drought exposure and field characteristics. Only a minority of fields experienced significant drought during the growing season: about 16% of observations faced moderate drought (D1), and 10% encountered this severity of drought during the critical silking stage. More severe drought at silking was rare; roughly 4% of fields had a severe drought (D2) and under 1% experienced extreme-or-worse drought (D3–D4) at that stage. Consistent with the reliance on rainfall in most U.S. corn production, only 6% of sample fields had access to irrigation. Moreover, field terrain is generally favorable: over three-quarters of fields are nearly level or have only moderate slopes. Overall, these descriptive patterns suggest that our analysis covers primarily rainfed corn operations on relatively flat land, where drought risk is present but not ubiquitous. This context—moderate DT adoption, with most fields otherwise utilizing conventional risk-management practices (crop insurance, traited seeds, irrigation if available)—helps set the stage for the regression and simulation results that follow.

5. Results

5.1 Effects of Drought Tolerance on the Distribution of Operating Profits

We begin by examining estimates from the flexible translog profit function (Table 2, columns 1-4), which serves as a second-order approximation to the unknown profit function. The key takeaway from the translog estimates is that the first-order effects (e.g., the linear coefficients on the prices and quasi-fixed factors) are economically sensible and broadly in line with those from the Cobb–Douglas (CD) model (columns 5-8). For example, increases in seed, fertilizer, or fuel costs reduce per-acre profit, and the DT trait coefficient is positive, though marginally significant (as expected). Moreover, the relative magnitudes of the first-order effects suggest intuitive substitution patterns: the seed price has the largest negative association with profit, followed by fertilizer, then diesel—consistent with the fact that seed and fertilizer expenditures comprise the largest shares of operating costs (Saavoss et al., 2021; Gillespie et al., 2025).[17] In short, the translog estimates reassure us that the CD functional form is not grossly

[17] Readers are referred to forthcoming companion work (McFadden et al., 2025) in which dual Morishima Elasticities of Substitution are computed from translog production functions estimated on similar data. That study finds drought tolerance to be complementary with irrigation and weakly substitutable with conservation tillage. That

misspecified at the sample mean. Given this, and for ease of interpretation, we focus our discussion on the more parsimonious CD results while noting differences where appropriate.

The regression estimates provide mixed evidence on the mean profit advantage of DT corn, but they reveal important differences across weather conditions and in profit variability. In the C-D profit models (Tables 2), the coefficient on DT adoption is positive but relatively small in magnitude and not consistently significant. For instance, depending on specification, the DT trait is associated with about a 0.06 to 0.23 increase in the inverse hyperbolic sine of profit per acre. In our sample, this amounts to an economically modest gain, on the order of a few tens of dollars per acre.[18] These small average effects are consistent with agronomic findings that DT hybrids confer little to no yield boost under normal conditions (and could incur a cost penalty) (Adee et al., 2016; Lee et al., 2014). They are also consistent with the hypothesis that U.S. farmers adopting DT seeds are paying a premium primarily for insurance value rather than for higher average yield. Supporting this, the regressions find little evidence of substantial endogeneity bias surrounding DT adoption: the generalized residuals are insignificant (columns 5 and 7) and their inclusion does not materially change the DT coefficient, suggesting that any unobserved factors correlated with both DT adoption and per-acre profitability are not heavily biasing the average effect. (See Appendix, Table A1 for first-stage regression results used to construct the generalized residuals.)

Looking at the mean effects of the quasi-fixed factors and controls, we find results that generally accord with broader sectoral patterns in U.S. corn production. For example, capital recovery (as a proxy for machinery and equipment investment) has a large positive effect, implying that better-capitalized operations enjoy higher per-acre profits, perhaps reflecting efficiencies brought about by having a more advanced capital stock. The coefficient on irrigation access is slightly negative and marginally significant in one specification, suggesting that fields with irrigation could have lower profits on average, all else equal.[19] Farmer experience is positive but insignificant, as is the indicator for other G.E. traits (HT or Bt), which suggests that, conditional on other inputs, stacking these traits with DT does not dramatically change average profit—not surprising given that nearly all fields in our sample use some GE traits. Finally, we observe that crop insurance participation is associated with substantially higher mean. While

finding is consistent with the notion, more common among Extension staff in the drier locations of the Great Plains states, that farmers may find it advantageous to employ multiple tools and management practices to protect under increasingly common and/or severe drought.

[18] Although it is straightforward to apply the inverse hyperbolic sine to the predicted values and residuals of the regressions to compute marginal effects (Bellemare and Wichman, 2020), our emphasis will be on the signs and relative magnitudes of the coefficients and how they compare with economic intuition and the related literature.

[19] One possible explanation is that irrigated fields often have higher input costs (e.g., pumping, energy) that can weigh on net profitability in a normal year—a point to which we will return when examining drought-specific outcomes.

perhaps counterintuitive at first glance, this result could reflect situations in which insured farmers pursue higher-return strategies knowing they have downside protection.[20]

While the average profit differences are small, the regression results point to state-contingent benefits of DT seeds under drought conditions. Unlike the first set of specifications in Table 2, those in Table 3 introduce interactions between DT and drought-related variables in the mean to capture heterogeneity in the trait's effectiveness. In these more granular models, the (insignificant) standalone DT effect on profit remains near zero (and even slightly negative in some cases), but this masks offsetting effects across weather states. Under non-drought conditions, DT adopters do not earn higher profits than non-adopters; if anything, point estimates suggest a slight shortfall, consistent with paying a seed premium without a yield benefit. By contrast, under drought conditions, there are indications of a protective effect. For example, in specification (4), the mean effect of interaction term DT × D1 drought is positive, with a negative (though insignificant) level effect of D1. This point estimate implies that during moderate drought years, DT adopters may have smaller profit declines than their counterparts, even if our sample lacks the precision to firmly establish a mean difference (with respect to the D1 level effect).[21] Nonetheless, the direction of the estimates is consistent with DT seeds cushioning profits under water-stressed circumstances, even if the mean impact under moderate drought is noisily estimated.

Of more interest is the effect of DT adoption on the distribution and riskiness of profit outcomes. The CD models in Table 3 include the second set of coefficients that describe how DT influences the variance of profit (columns 1b-5b). We see evidence that DT seeds reduce downside risk: drought conditions substantially increase profit variability, as indicated by large positive coefficients on the various drought measures, but DT adoption attenuates this volatility. The interaction DT × average PMDI is negative and highly significant (column 1b), indicating that as drought severity rises, DT seeds blunt the increase in profit variability. This effect is perhaps most pronounced for moderate droughts occurring at critical growth stages. For instance, a moderate drought during the silking stage could raise profit variance for conventional corn (reflecting the heightened downside risk), but DT adopters see a much smaller variance increase. The coefficient on DT × silking-stage D1 drought in the variance equation is -3.17 and statistically significant at the 1% level. By contrast, under more extreme drought stress (e.g., a severe D2 drought), the estimates show little mitigation—the interaction is small and insignificant,

[20] It may also capture unobserved differences in management; for example, more sophisticated or financially secure farmers both buy insurance and achieve higher yields and profits. In any case, the positive association between insurance and profitability aligns with recent findings that insurance could incentivize more intensive input use or risk-taking that raises expected returns (e.g., Goodwin and Piggott, 2020).

[21] The lack of a significant positive interaction in the mean equation could be due to insufficient power (since truly severe droughts were infrequent in the sample) or because moderate drought conditions in the data were not severe enough to elicit a large average yield gap between DT and conventional hybrids.

suggesting that when droughts are severe enough to cause crop failure, DT hybrids offer little assistance, in line with Lybbert and Carter (2015).

Figure 3 further illustrates these distributional differences by plotting the empirical cumulative distribution functions (CDFs) of per-acre profit for adopters and non-adopters under moderate (D1) drought versus non-drought conditions. The CDFs suggest a first-order stochastic dominance in favor of DT adoption when drought occurs. Under moderate drought conditions, the profit distribution for DT adopters is shifted to the right of that for non-adopters, suggesting that adopters are relatively less likely to suffer lower profits (or losses) during drought. The left tail of profits is thinner for adopters, reflecting fewer highly adverse outcomes. Moreover, the median and upper quantiles of profit are also slightly higher for adopters in drought conditions, indicating they also tend to achieve somewhat better revenues on average under such conditions. By contrast, in years with favorable weather (no drought), the profit distributions for DT and non-DT fields are highly similar. If anything, there is a hint that DT adopters might underperform slightly in good years, consistent with a hypothesis of a mild yield drag or additional seed cost effects trimming the highest profits, though these differences are minute.

The figure also stratifies predicted outcomes by irrigation status, confirming that DT's value is greatest for rainfed fields. Among DT adopters facing drought, those with irrigation exhibit higher profits and less variability than those relying solely on rainfall. This is expected—irrigation is a direct substitute for rainfall—but it highlights that DT is not a panacea for severe moisture deficits on unirrigated land. The CDFs show that irrigated DT adopters have stochastically dominant profits relative to non-irrigated DT adopters under drought. For a non-irrigated DT field, drought still causes a noticeable leftward shift in profits—though notably less of a shift than it would under a non-DT variety. Thus, DT traits and irrigation both reduce downside risk; when used in combination, risk is presumably lowest but at added cost, and when irrigation is absent, the DT trait alone provides partial protection.

Taken together, the regression evidence and profit distributions imply that on average, DT corn does not raise mean profits in a typical year, but it significantly reduces the dispersion of outcomes by mitigating losses during drought. Thus, the technology's economic significance lies in risk management. Even if the average profit effect is close to zero, the value of avoiding tail-risk outcomes can be substantial for farmers. By helping to stabilize yields, we would expect such technologies to increase the certainty-equivalent of profit. We turn next to a formal evaluation of this risk-reduction benefit using a simulation of risk-adjusted welfare metrics.

5.2 Risk-Adjusted Net Benefits Simulations

To quantify the value of DT corn in an uncertain environment, we simulate farmers' certainty equivalents (CEs) under different scenarios and levels of risk aversion, drawing on the estimates from our profit

models. In essence, we ask how much would a risk-averse farmer be willing to pay for the risk buffering provided by DT seeds, and does this value exceed the incremental cost of the seeds?

The per-acre net benefit results (Table 4) show that the average U.S. corn farmer realizes only a small risk-adjusted benefit from DT adoption at low levels of risk aversion, but this benefit grows for more risk-averse preferences. For a near risk-neutral farmer ($\rho = 0.005$), the median difference in CEs between adopting and not adopting DT is about \$2.40/ac and not statistically significant. In other words, a farmer with very low risk aversion is indifferent to the DT trait—the slight reduction in profit volatility is worth only a few dollars per acre to them, which is on the same order as the trait's cost. However, for a moderately risk-averse farmer ($\rho = 0.01$), the risk-adjusted gain from DT averages \$5.19/ac, and for a higher (but still plausible) risk aversion level ($\rho = 0.02$), the gain is roughly \$5.94/ac. These results are from Panel A, which does not allow for interaction effects between DT and irrigation (access), though this is relaxed in the specification underlying Panel B (with similar results).

Kernel density estimates of the differences in CEs across instances of drought by risk aversion coefficient are shown in Figure 4. As expected, as farmers become more risk-averse (moving from $\rho = 0.005$ to $\rho = 0.020.02$), the entire distribution of risk-adjusted benefits shifts to the right. At a moderate to high level of risk aversion, the kernel densities are largely concentrated in positive territory, implying that a large majority of U.S. farmers would experience a positive gain in utility from adopting DT.

These dollar magnitudes are modest in absolute terms, equating to only a few percentage points of average per-acre revenue, yet they are economically important when compared to the DT seed cost. Our hedonic price analysis (see Appendix, Table A2) finds that seed with the DT trait commands roughly a \$5/ac premium. Thus, for a farmer with moderate risk aversion, the CE improvement from DT roughly covers its added cost. In other words, at $\rho = 0.01$ or $\rho = 0.02$, the risk-adjusted benefit (\$5–6) is on par with the trait's price, implying the technology "pays for itself" in utility terms. This mirrors the classic result in the literature on insurance adoption suggesting that the risk premium drives willingness-to-pay (e.g., Einav and Finkelstein, 2011). Our findings indicate that U.S. corn farmers, on average, value the embedded insurance at roughly the market price of the trait, helping to explain current adoption patterns.

However, these average CE gains conceal large differences across weather realizations. Table 4 breaks out the risk-adjusted benefit of DT adoption under four scenarios: $(DT, Drought) = (0,0), (0,1), (1,0), (1,1)$. The CE difference between adopting and not in each scenario is close to zero in non-drought years but much larger in drought years. Specifically, for $\rho = 0.02$, we estimate virtually no risk-adjusted benefit in a normal year. If no moderate drought occurs, a DT adopter's CE is actually about \$0.30 lower than if they had not adopted (though insignificant). However, if a drought were to have occurred, the certainty-equivalent of profit is substantially higher with DT: a \$15.93/ac gain for a non-adopter who counterfactually had DT during the drought, and a \$22.08/ac gain for an actual DT adopter in

a drought relative to if they had planted a conventional hybrid. This kind of state-contingent pattern underscores the nature of DT a kind of shallow-loss insurance policy. Notably, this aligns with farmers' subjective experiences documented by Boucher et al. (2024). In a randomized trial, farmers who experienced a drought and saw DT seeds protect their harvest responded by increasing investment in the technology thereafter, whereas those who did not see a drought backed away from using them in the following season. In other words, the occasional and contingent nature of DT's benefits means farmers only witness its value episodically, helping to explain why adoption may stall in stretches of good weather, reflective of the learning problem noted in the DT-related index insurance literature.

It is also useful to compare the risk-adjusted benefit to the direct profit effect (ignoring risk preferences). Table 5 presents this comparison aggregated to the U.S. Under the realized 2021 adoption rate, the average per-acre profit was only $2.61 higher due to DT adoption (Panel A). This corresponds to an aggregate increase of roughly $49 million in farm profits nationwide attributed to DT, given the weather that occurred. Most of this profit gain accrued to fields that faced drought conditions in that year; those fields experienced sizable profitability boosts from DT, whereas fields that did not experience drought saw no gain or a small loss (the seed cost). On the whole, from a risk-neutral perspective, the ex post realized benefit of DT in 2021 was positive but small—less than 1% of that year's total corn sector revenue (USDA-ERS, 2025). However, under risk aversion, the value is quite different. The aggregate certainty-equivalent gain from DT under 2021 conditions is estimated at $19 million—lower than the $49 million profit gain because risk-averse valuation penalizes upside and puts weight on downside protection. The $19 million figure can be interpreted as the monetary equivalent of the welfare improvement that U.S. corn growers derived from DT traits in 2021. While not enormous in the context of the entire farm economy, this is a non-negligible benefit, realized despite the fact that roughly only 25% of U.S. acres had adopted DT.

If we scale up adoption locally, the benefits grow approximately proportionally. In Table 5, we simulate counterfactual scenarios with 5%, 10%, and 20% higher DT adoption (holding total 2021 corn acreage constant, as well as the distribution of drought). Under a 20% increase in adoption (i.e., a 31% adoption rate), the annual risk-adjusted welfare gain increases to $23 million. The corresponding aggregate profit gain in that scenario is about $59 million. These projections suggest there could still be unexploited risk management gains at the margin if more farmers adopt DT, though there would likely exhibit diminishing marginal returns if adopters are increasingly on low-risk (well-watered or irrigated) acres. Indeed, if additional adoption comes from farmers in regions that rarely experience drought, the incremental risk reduction would be minimal and the aggregate CE gain per new acre would be low. Yet, if adoption were to intensify in high-drought-frequency regions, the marginal benefits would be larger. Our national-level estimates assume the additional adoption is spread proportionately across drought-

prone and drought-free areas (hence roughly linear gains). In reality, one might expect that as adoption expands, it will penetrate more marginal areas where the value of DT is lower, potentially flattening the benefit curve. Conversely, an intensification of extreme weather could increase drought frequency in currently "safe" areas, raising future benefits of broad adoption.

Finally, it is worth comparing the magnitude of DT's risk reduction to other risk management tools. The small increase in certainty-equivalent income we find (for moderate risk aversion in a drought-prone context) is of similar order of magnitude to the gain from other interventions in some studies. Lybbert and Carter (2015), for example, simulate that DT maize would raise CE by about 6.1% in a representative setting, compared to roughly 2–3% for typical index insurance, and around 7.2% if both were combined. In our case, the use of DT provides a meaningful, though smaller, risk-reducing benefit. There remains a gap in protection for the most extreme events, which suggests a role for complementary strategies to insure against more severe droughts. Our analysis thus complements related findings that bundling genetic and financial risk management can be synergistic (e.g., Boucher et al., 2024).

6. Conclusion

This study has sought to quantify the risk-related economic benefits of DT corn by estimating theoretically-grounded profit functions and simulating risk-adjusted returns using U.S. field-level data. In particular, we have modeled per-acre operating profit as a function of DT hybrid adoption (controlling for its potentially endogenous use), variable input prices, and quasi-fixed factors (including other risk-management tools), allowing the DT trait to affect both the mean and variance of profits. Using a straightforward expected utility framework, we have computed certainty equivalents (CEs) for adopters and nonadopters under differing drought conditions, comparing them to DT seed premiums generated from hedonic price regressions. Our analysis has drawn on nationally representative USDA microdata (the 2016 and 2021 waves of the ARMS), providing a broad empirical basis to evaluate how DT corn performs across diverse farm conditions. As such, these methods have enabled us to estimate among the first set of nationally representative average profit effects, as well as the technology's value in reducing downside risk under drought and to simulate aggregate outcomes under various adoption levels.

Our results indicate that adopting DT corn hybrids confers modest but positive gains in profitability on average, and more substantial risk mitigation benefits under drought stress. Point estimates show a small increase in mean operating profit per acre for DT adopters relative to conventional seed users (on the order of a few dollars/ac), suggesting that the trait's impact on average profit is minimal in non-drought environments. However, this average masks important state-contingent benefits: under moderate drought scenarios, fields with DT hybrids realized substantially higher profits and higher CEs than comparable non-DT fields. As expected, DT corn helps buffer profits when rainfall is scarce,

aligning with the trait's intended purpose. These risk-adjusted benefits are especially pronounced for farms that actually experienced drought during the growing season. Consistent with these per-acre findings, our counterfactual simulations show that aggregate farm welfare (in a risk-adjusted sense) rises as DT adoption expands. The magnitude of these aggregate gains is again, but they underscore that wider diffusion of DT technology would have positive net benefits for the sector as a whole under reasonable drought expectations. These benefits would accrue primarily in years and regions with water stress, reinforcing that the value of DT traits materializes most in drought-prone environments and remains limited under favorable weather.

While our findings support the role of DT corn as a risk-mitigating input, we emphasize several caveats and limitations. First, the analysis is based on cross-sectional data (two survey years) rather than panel observations, which constrains our ability to observe variance effects directly over time. We infer risk reduction from modeled variance and utility, but without tracking the same fields across multiple seasons, we cannot fully capture how DT adoption consistently affects profit volatility. Unobserved heterogeneity—for example, if more skilled or risk-tolerant farmers select into DT—could bias our results, even though we attempted to control for such factors. In short, the cross-sectional nature of our data may not fully reflect the true interannual risk-reduction impact of DT traits. Second, our counterfactual welfare simulations necessarily rely on simplifying assumptions. We assumed a fixed DT seed price premium (based on a hedonic pricing model) and specific farmer risk preference parameters (constant absolute risk aversion) when calculating CEs. We also held the incidence and timing of drought conditions constant in the adoption scenarios. These assumptions, while grounded in available data, introduce uncertainty: different seed cost scenarios, distributions of risk aversion, or spatiotemporal drought patterns could lead to different benefit estimates. However, the qualitative conclusions—that DT has provided insurance-like value under drought and modest average gains in U.S. corn production—are robust, but precise dollar values and aggregate impacts could vary under alternative assumptions.

There are several promising avenues for future research. One priority is to incorporate panel data into similar analyses of U.S. corn production, which would enable a more definitive identification of variance reduction induced by DT adoption. Second, further work could refine the modeling of seed costs and premiums associated with DT traits. Our analysis used a hedonic regression to estimate the average trait premium, but more detailed research into seed pricing (how premiums vary by region, seed type, or over time as the technology matures) would improve the accuracy of net benefit calculations. This could involve incorporating seed company pricing strategies or farmers' willingness-to-pay for risk reduction into the evaluation. Third, an important extension would be to integrate these results into broader risk management frameworks or insurance contexts. For example, a more complete understanding of how DT adoption interacts with crop insurance decisions could result in improved insights that connect

technological and financial risk mitigation strategies. Likewise, incorporating DT-traited seeds into farm-level risk models or simulations of farmers' portfolio choices (including irrigation, insurance, and related investments) could reveal synergies or trade-offs between such tools. By situating DT crops within the wider set of risk management options, future research could provide a more comprehensive assessment of their role in agricultural resilience.

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Table 1. Summary Statistics

Variable	Unit	Mean	Std. Error	5th Perc.	95th Perc.
Operating profit	$ (2021)/ac	406.97	7.24	16.30	783.7
DT, current season	{0,1}	0.24	0.02	0	1
DT, last season	{0,1}	0.04	0.01	0	1
Seed price	$ (2021)/1000 seeds	3.49	0.03	1.84	4.97
Fertilizer price	$ (2021)/lb	0.73	0.02	0.26	1.94
Diesel price	$ (2021)/machine	90.45	2.11	7.56	248.98
Corn price	$ (2021)/ac	4.73	0.02	3.72	5.91
Irrigation access	{0,1}	0.06	0.01	0	1
Field experience	Years	22.7	0.44	3	47
Capital recovery	$ (2021)/machine	1,119	24.5	47	3,309
D1 drought	{0,1}	0.16	0.02	0	1
PMDI, average	{0,1}	-1.14	0.06	0	1
PMDI, maximum	{0,1}	0.36	0.06	0	1
D1 drought at silking	{0,1}	0.10	0.01	0	1
D2 drought at silking	{0,1}	0.04	0.01	0	1
D3 drought at silking	{0,1}	0.01	0.001	0	1
D4 drought at silking	{0,1}	0.001	0.001	0	1
GE traits, HT or Bt	{0,1}	0.95	0.01	0	1
Slope, nearly level	{0,1}	0.43	0.02	0	1
Slope, moderate and uniform	{0,1}	0.35	0.02	0	1
Slope, moderate and variable	{0,1}	0.19	0.01	0	1
Slope, steep and uniform	{0,1}	0.02	0.01	0	1
Slope, steep and variable	{0,1}	0.01	0.01	0	1
Soil texture, loam	{0,1}	0.36	0.02	0	1
Soil texture, clay	{0,1}	0.17	0.01	0	1
Soil texture, sandy	{0,1}	0.05	0.01	0	1
Soil texture, mixed or silty	{0,1}	0.42	0.02	0	1
Highly erodible land	{0,1}	0.18	0.01	0	1
Wetland area	{0,1}	0.03	0.01	0	1
April-September temp. deviation	° C	0.83	0.01	0.35	1.24
April-September precip. deviation	mm	96.39	4.68	-135.36	300.78
Crop insurance	{0,1}	0.87	0.01	0	1
Corn enterprise size	Acres	714	42.8	40.6	2215
Field acres seeded	Acres	59.2	1.32	3.5	156

Note: Std. Error = standard error, perc. = percentile. Sample size = 1,723 fields. All estimates have been weighed using the ARMS expansion factor. Minimums and maximums have been suppressed. See 5th and 95th percentiles for illustration of data spread.

Table 2. Effects of Drought Tolerance on the Mean and Variance of Per-Acre Operating Profits

	(1) Translog	(2) Translog	(3) Translog	(4) Translog	(5) Cobb-Douglas	(6) Cobb-Douglas	(7) Cobb-Douglas	(8) Cobb-Douglas
Mean Effects								
ln(Seed Price) (S)	-2.526***	-3.060***	-1.192*	-1.733**	-0.408***	-0.337***	-0.331***	-0.315***
ln(Fertilizer Price) (F)	-1.323***	-1.043**	-1.943***	-1.586***	-0.292***	-0.321***	-0.338***	-0.421***
ln(Diesel Price) (W)	-0.758*	-0.271	-0.809	-0.400	-0.113**	-0.092*	-0.123	-0.195***
DT (D)	1.655*	1.310**	1.710*	1.010	0.055	0.226***	0.147	0.143*
Irrig. Access (I)	1.107	0.089	2.193	-0.384	-0.328*	-0.098	-0.338	-0.016
ln(Experience) (E)	-0.874***	-0.524	-0.408	-0.033	-0.019	-0.034	0.014	0.075
ln(Capital Recovery) (C)	-0.962***	-0.802**	-0.551	-0.315	0.129***	0.151***	0.140**	0.234***
Ht or BT Traits	0.633	0.751	0.016	0.120	-0.408	0.648	0.475*	0.171
Crop Insurance	1.372***	1.375***	1.063***	1.052***	1.252**	0.969**	0.448*	0.827***
Gen. Resid: D	-0.242	--	-0.414	--	0.090	--	-0.004	--
Gen. Resid: D x I	-0.142	--	-0.140	--	--	--	--	--
Gen. Resid: D x E	-1.309	--	-0.754	--	--	--	--	--
Gen. Resid: D x S	5.903***	4.500***	5.851***	4.231***	--	--	--	--
Gen. Resid: D x F	-2.440**	-0.740	-2.379***	-0.663	--	--	--	--
Gen. Resid. D x W	-0.316	--	-0.493	--	--	--	--	--
Variance Effects								
DT	-0.239	-0.150	0.031	0.046	-0.148	-0.503	-1.036**	-0.066
DT x D1 Drought	-2.295	-2.525	-2.107	-2.460	-2.488	-2.654*	-0.673	-2.605
D1 Drought	0.600	0.624	0.660	0.694*	0.505	0.956**	0.584**	0.740**
Irrig. Access (I)	1.218*	1.257**	1.194*	1.301**	1.202*	0.985	1.590***	1.099*
ln(Experience) (E)	0.100	0.107	-0.095	-0.078	0.039	0.094	0.163	-0.126
HT or Bt Traits	-1.847***	-1.848***	-0.506	-0.494	-1.742***	-1.583***	-1.279**	-0.327
Crop Insurance	-2.142	-2.159*	-1.655*	-1.636*	-2.164	-1.757	-1.198	-1.490*
Gen Resid: D	0.014	--	-0.027	--	-0.027	--	0.465	--
Gen Resid: D x D1 Drought	-0.059	--	-0.150	--	-0.050	--	-0.075	--
Year FE and State FE	Y	Y	Y	Y	Y	Y	Y	Y
Soil, Weather, Structure, Dem. Controls	Y	Y	Y	Y	Y	Y	Y	Y
Translog terms	Y	Y	Y	Y	N	N	N	N
Survey Weights	Y	Y	N	N	Y	Y	N	N
Obs.	1,634	1,637	1,634	1,637	1,634	1,723	1,634	1,723
Wald χ^2 statistic	226.3***	220.0***	440.4***	427.9***	188.9***	186.6***	358.0***	378.9***
Test of $\ln(\sigma^2) = 0$	25.0***	24.8***	214.5***	224.3***	26.6***	22.5***	229.6***	233.6***

Note: Translog square and cross-product terms, other controls, and bootstrap standard errors (B = 2,000) are not shown for space considerations. The inverse hyperbolic sign transformation has been applied to the dependent variable in order to keep instances of negative per-acre operating profits. To reduce the influence of outliers, the dependent variable, prices, experience, capital recovery, and weather deviations have been winsorized. Monotonicity of the translog profit functions with respect to the three prices holds at the sample means. Significance is denoted as *** p <0.01, ** p <0.05, * p <0.10.

Table 3. Heterogeneity of Drought Tolerance Effects on Mean and Variance of Per-Acre Operating Profits

	(1a)	(2a)	(3a)	(4a)	(5a)	(1b)	(2b)	(3b)	(4b)	(5b)
			Mean Effects					**Variance Effects**		
DT (D)	0.080	0.064	-0.012	-0.025	-0.003	-0.231	-0.219	0.022	0.028	0.110
Irrig. Access (I)	0.128	0.107	0.037	0.060	0.054	0.595	0.550	0.584	0.635*	0.897
DT x Avg. PMDI	0.014	--	--	--	--	-0.009***	--	--	--	--
Avg. PMDI	-0.048	--	--	--	--	0.158*	--	--	--	--
DT x Max PMDI	--	0.011	--	--	--	--	-0.031	--	--	--
Max PMDI	--	0.005	--	--	--	--	0.100*	--	--	--
DT x Silking D1 Drought	--	--	0.440	--	--	--	--	-3.172***	--	--
DT x Silking D2 Drought	--	--	0.340	--	--	--	--	0.287	--	--
Silking D1 Drought	--	--	-0.157	--	--	--	--	0.377	--	--
Silking D2 Drought	--	--	-0.325	--	--	--	--	-0.100	--	--
Silking D3 Drought	--	--	-1.431	--	--	--	--	2.686***	--	--
Silking D4 Drought	--	--	-7.819***	--	--	--	--	0.478	--	--
DT x D1 Drought	--	--	--	0.623***	0.547***	--	--	--	-1.803**	-1.880**
D1 Drought	--	--	--	-0.343	-0.360	--	--	--	0.810**	0.842***
DT x Irrig. Access	--	--	--	--	0.028	--	--	--	--	-3.335**
Year FE and State FE	Y	Y	Y	Y	N	N	N	N	N	N
Other Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Translog Terms	N	N	N	N	N	N	N	N	N	N
Survey Weights	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control Functions	N	N	N	N	N	N	N	N	N	N
Obs.	1,723	1,723	1,718	1,723	1,723	1,723	1,723	1,718	1,723	1,723
Wald χ^2 statistic	164.6***	175.4***	506.9***	203.7***	220.5***	164.6***	175.4***	506.9***	203.7***	220.5***
Test of $\ln(\sigma^2) = 0$	20.4***	17.4**	54.2***	20.49***	22.0***	20.4***	17.4**	54.2***	20.49***	22.0***

Note: All regressions are performed using the Cobb-Douglas specification. PMDI values have been mapped into Drought Monitor categories using standard thresholds. In columns (1) and (2), PMDI has been rescaled so that larger values indicate worse drought conditions. The inverse hyperbolic sign transformation has been applied to the dependent variable in order to keep instances of negative per-acre operating profits. To reduce the influence of outliers, the dependent variable, prices, experience, capital recovery, and weather deviations have been winsorized. Other controls include the soil, weather, structure, and demographic controls from Table 2. Standard errors have been clustered at the county level. Significance is denoted as *** p <0.01, ** p <0.05, * p <0.10.

Table 4. Per-Acre Risk-Adjusted Benefits of Drought Tolerance under CARA Utility (ΔCE)

A. No DT x I terms					
Coeff of Abs. RA (ρ)	**Avg.**	**(DT, Dr) = (0,0)**	**(DT, Dr) = (0,1)**	**(DT, Dr) = (1,0)**	**(DT, Dr) = (1,1)**
0.005	\$2.40	-\$1.97	\$9.02	-\$1.79	\$14.45*
	(\$3.37)	(\$3.64)	(\$8.38)	(\$3.61)	(\$8.37)
0.01	\$5.19*	-\$0.84	\$14.71**	-\$0.67	\$20.78**
	(\$2.72)	(\$2.8)	(\$7.25)	(\$3.02)	(\$8.71)
0.02	\$5.94	-\$0.32	\$15.93**	-\$0.26	\$22.08**
	(\$3.31)	(\$3.48)	(\$6.37)	(\$3.80)	(\$9.60)
B. With DT x I terms					
Coeff of Abs. RA (ρ)	**Avg.**	**(DT, Dr) = (0,0)**	**(DT, Dr) = (0,1)**	**(DT, Dr) = (1,0)**	**(DT, Dr) = (1,1)**
0.005	\$2.43	\$0.51	\$5.56	-\$0.53	\$10.60
	(\$3.64)	(\$4.00)	(\$8.35)	(\$3.86)	(\$8.83)
0.01	\$4.85*	\$0.26	\$11.97	\$0.12	\$18.15*
	(\$2.81)	(\$2.82)	(\$7.55)	(\$2.95)	(\$9.46)
0.02	\$5.69*	-\$0.03	\$14.11**	\$0.26	\$20.54**
	(\$3.36)	(\$3.42)	(\$6.82)	(\$3.66)	(\$10.24)

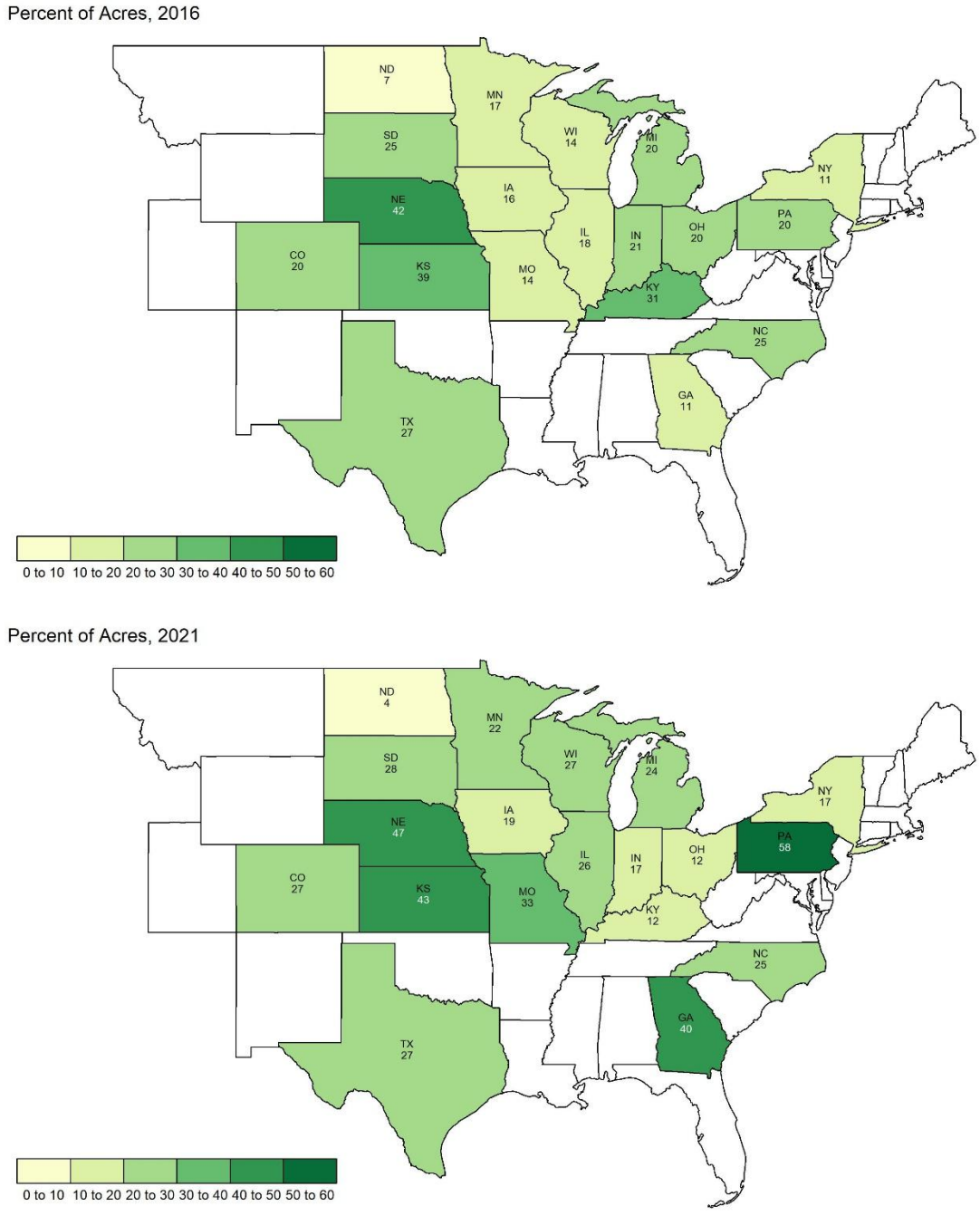
Note: Coeff of Abs. RA = coefficient of absolute risk aversion (ρ), Avg. = average (i.e., estimated on full sample), DT = indicator of drought-tolerant corn adoption, and Dr = drought (an indicator of moderate drought, D1). Estimates are created by simulating per-acre profits using 1,000 draws from normal distributions having means and standard deviations corresponding to models (4) and (5) from Table 3. To reduce sensitivity to outliers, all utility draws have been winsorized. The first set of entries are median values, calculated as the difference in certainty equivalents between adopters and nonadopters. Bootstrapped standard errors (B = 1,000) are in parantheses.

Table 5. Aggregate Risk-Adjusted Net Benefits and Profitability Effects of Drought Tolerance, Realized and Counterfactual Scenarios

Panel. A. No DT x I terms	**Risk Adjusted Net Benefit ($\Delta CE - Prem$)**					**Predicted Profit Differences ($\pi_{DT=1} - \pi_{DT=0}$)**				
Per-Acre (2021 USD)	**Avg**	**(DT, Dr) = (0,0)**	**(DT, Dr) = (0,1)**	**(DT, Dr) = (1,0)**	**(DT, Dr) = (1,1)**	**Avg.**	**(DT, Dr) = (0,0)**	**(DT, Dr) = (0,1)**	**(DT, Dr) = (1,0)**	**(DT, Dr) = (1,1)**
Realized	1.02	-5.19	10.71	-5.19	17.31	2.61	-1.63	24.28	-1.66	25.77
	[0.8, 1.2]	[-5.4, -4.9]	[10.2, 11.2]	[-5.6, -4.8]	[16.2, 18.5]	[1.7, 3.5]	[-1.7, -1.6]	[22.9, 25.6]	[-1.8, -1.6]	[22.1, 29.4]
Aggregate (Mil. 2021 USD)										
Realized	19	-157	244	-70	91	49	-49	554	-22	136
	[16, 23]	[-164, -149]	[233, 256]	[-76, -64]	[85, 98]	[32, 65]	[-51, -47]	[523, 585]	[-24, -21]	[117, 155]
+5% adoption in 2021	20	-154	240	-73	96	51	-48	544	-23	143
	[16, 24]	[-161, -147]	[229, 251]	[-79, -67]	[90, 102]	[34, 69]	[-51, -46]	[513, 574]	[-25, -22]	[123, 163]
+10% adoption in 2021	21	-151	236	-77	101	54	-48	534	-25	150
	[17, 25]	[-159, -144]	[224, 247]	[-83, -70]	[94, 107]	[35, 72]	[-50, -45]	[504, 564]	[-26, -23]	[128, 171]
+20% adoption in 2021	23	-146	227	-84	110	59	-46	515	-27	163
	[19, 27]	[-153, -139]	[216, 238]	[-91, -76]	[102, 117]	[39, 79]	[-48, -44]	[486, 543]	[-29, -25]	[140, 187]
Panel B. With DT x I terms	**Risk Adjusted Net Benefit ($\Delta CE - Prem$)**					**Predicted Profit Differences ($\pi_{DT=1} - \pi_{DT=0}$)**				
Per-Acre (2021 USD)	**Avg**	**(DT, Dr) = (0,0)**	**(DT, Dr) = (0,1)**	**(DT, Dr) = (1,0)**	**(DT, Dr) = (1,1)**	**Avg.**	**(DT, Dr) = (0,0)**	**(DT, Dr) = (0,1)**	**(DT, Dr) = (1,0)**	**(DT, Dr) = (1,1)**
Realized	0.77	-4.90	8.89	-4.67	15.77	3.24	-0.17	20.87	-0.11	22.27
	[0.6, 9]	[-5.2, -4.6]	[8.4, 9.4]	[-5.1, -4.2]	[14.6, 16.9]	[2.5, 3.9]	[-0.2, -0.2]	[19.8, 22.0	[-0.2, -0.1]	[19.2, 25.4]
Aggregate (Mil. 2021 USD)										
Realized	14	-148	203	-63	83	60	-5	476	-1.5	118
	[11, 18]	[-156, -140]	[191, 214]	[-69, -57]	[77, 89]	[47, 74]	[-5.4, -5.0]	[451, 501]	[-2.1, -0.9]	[101, 134]
+5% adoption in 2021	15	-145	199	-66	88	64	-5	468	-1.6	123
	[11, 19]	[-153, -138]	[189, 210]	[-72, -60]	[81, 94]	[50, 78]	[-5.3, -4.9]	[443, 492]	[-2.2, -1.0]	[106, 141]
+10% adoption in 2021	16	-143	195	-69	92	67	-5	459	-1.7	129
	[12, 20]	[-150, -135]	[184, 207]	[-76, -62]	[85, 98]	[52, 81]	[-5.2, -4.8]	[435, 484]	[-2.3, -1.0]	[111, 147]
+20% adoption in 2021	17	-139	189	-75	100	73	-5	442	-1.8	141
	[13, 22]	[-145, -131]	[178, 199]	[-82, -68]	[93, 107]	[57, 89]	[-5.1, -4.6]	[419, 466]	[-2.5, -1.1]	[122, 161]

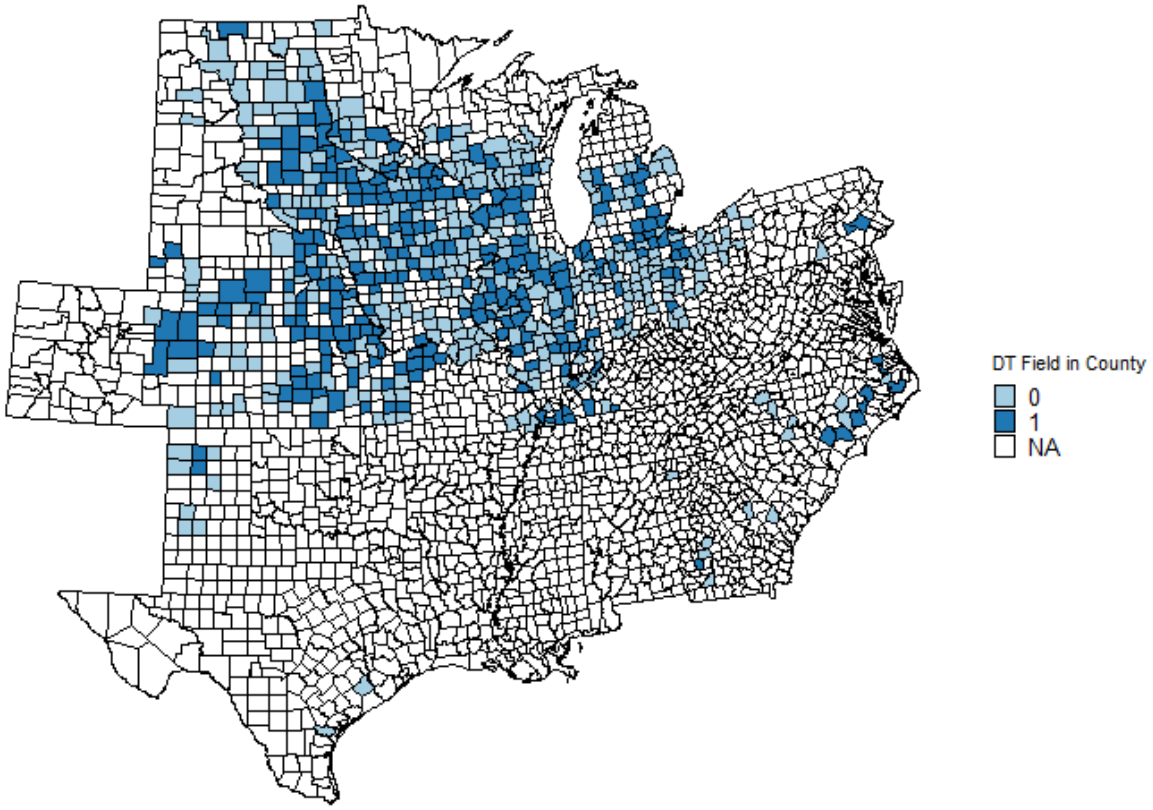
Note: Table entries are survey-weighted means corresponding to the full-sample average or one of four {DT, Dr} scenarios. Bracketed entries are 95% confidence intervals relying on jackknifed standard errors. Risk-adjusted net benefits are calculated using the certainty equivalent (CE) differentials corresponding to $\rho = 0.02$ from Table 4. For consistency with the CE calculations, profit differentials have been winsorized. DT premiums are calculated using model (6) from the hedonic price regressions detailed below in the Appendix, Table A1. For The three DT adoption scenarios hold U.S. corn acreage constant at its 2021 sample estimate of 71.7 million acres, implying increased in DT acres reduce non-DT acres.

Figure 1. Percent of State Corn Acreage Planted to Drought-Tolerant Hybrids, 2016 and 2021



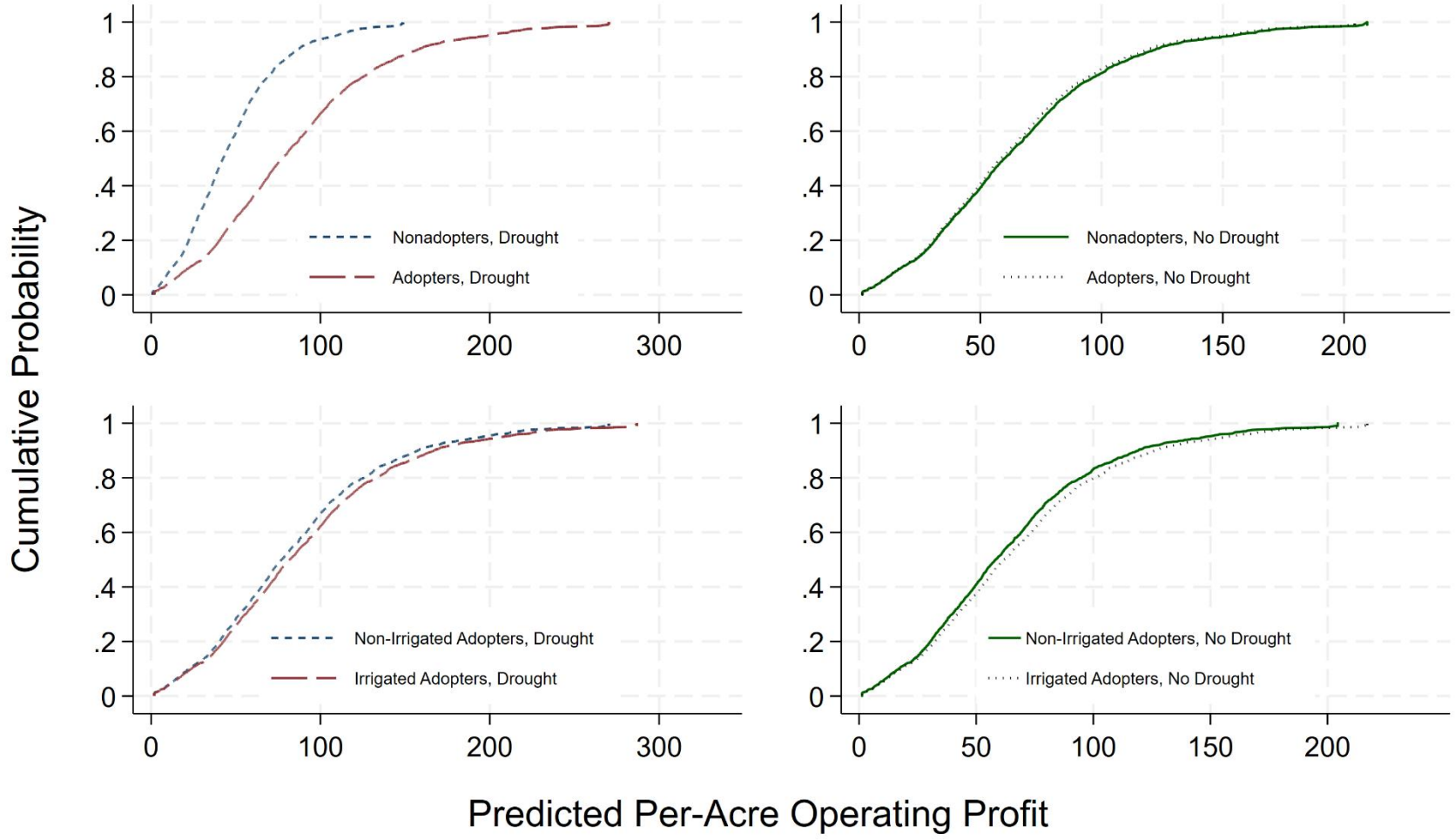
Note: In 2016, U.S. DT corn acreage planted totaled 18.6 million acres. In 2021, DT corn acreage planted totaled 22.5 million acres.

Figure 2. Distribution of ARMS DT Corn Fields by County



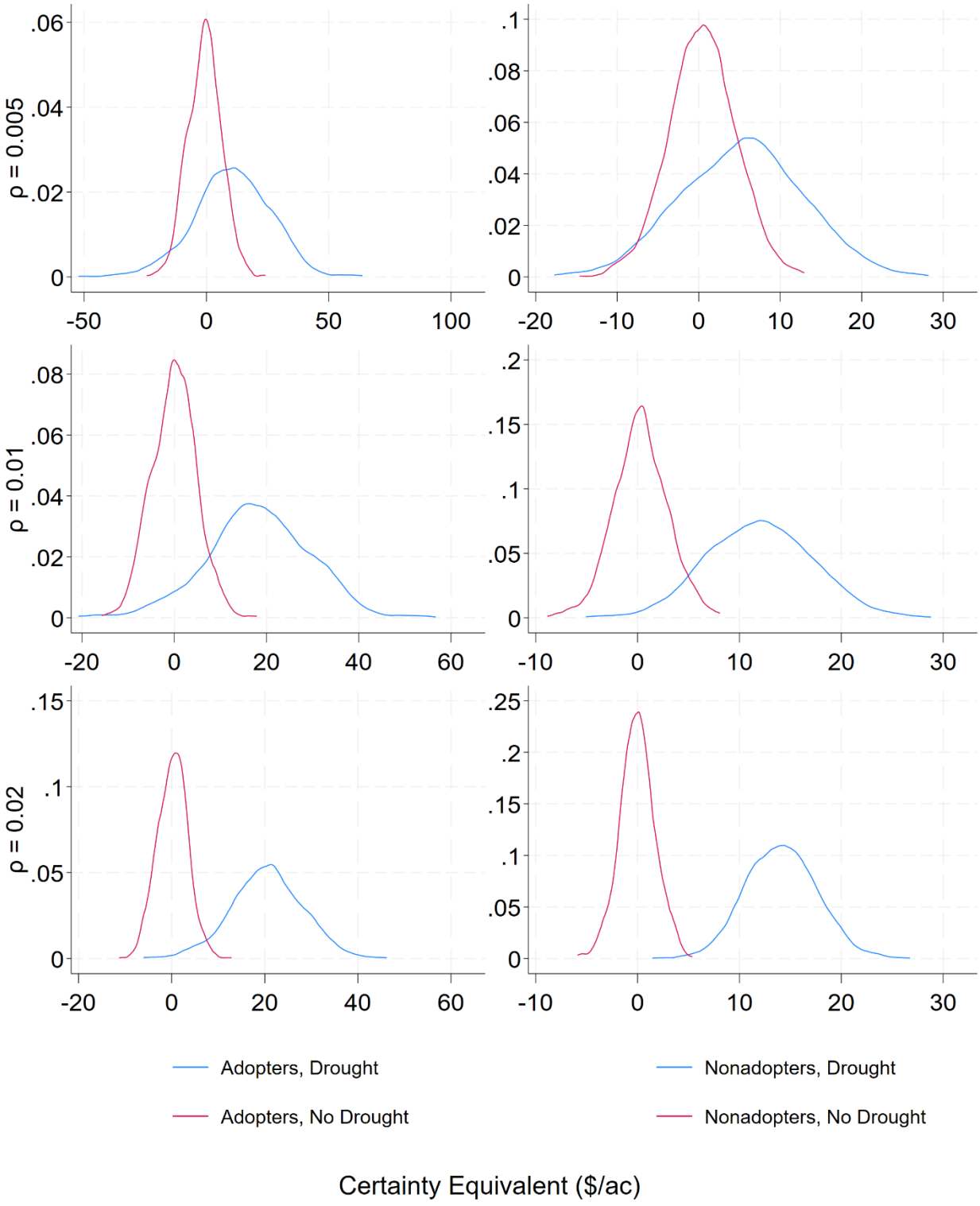
Note: Figure depicts the counties in our sample containing at least one field in USDA's 2016 or 2021 Agricultural Resource Management Survey (ARMS). In many instances, there are multiple fields per county, and among these counties, there can be several fields planted to DT varieties.

Figure 3. Empirical CDFs of Per-Acre Profits for DT Adopters and Nonadopters by Drought Status and Irrigation Access



Note: Figures illustrate the empirical cumulative distribution functions (eCDFs) of the differences in predicted per-acre profits between adopters and non-adopters by D1 drought status and between irrigated and non-irrigated adopters by drought status.

Figure 4. Kernel Densities of ΔCEs by DT Adoption and Drought Status



Note: ΔCertainty equivalents are calculated from 1,000 draws profits using 1,000 draws from normal distributions having means and standard deviations corresponding to the model (5) in Table 3. To reduce sensitivity to outliers, all utility draws have been winsorized prior to calculating the certainty equivalents. Densities have been computed using the Epanechnikov kernel.

Appendix. Control Function Estimates and Hedonic Seed Price Regressions

Table A1. First-Stage Regressions to Generate Control Functions

	Dependent Variable							
	DT	DT x I	DT x E	DT x C	DT x S	DT x F	DT x W	DT x D1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cont DT	2.650***	--	-0.489	-0.984	0.101	0.795	-0.422	1.216***
Cont DT x I	--	97.616	-0.106	-0.292	0.072	0.103	-0.243	--
Cont DT x E	--	4.095	0.593***	0.382	-0.039	-0.197	0.229	--
Cont DT x C	--	-11.704	-0.016	0.343	0.019	-0.044	-0.109	--
Cont DT x S	--	--	-0.240	-0.399	0.862***	0.333	-0.205	--
Cont DT x F	--	--	0.119	0.164	-0.008	0.621***	0.009	--
Cont DT x W	--	--	0.029	0.074	-0.035	-0.005	0.908***	--
Obs.	1,637	1,641	1,637	1,637	1,637	1,637	1,637	1,285
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	N	Y	Y	Y	Y	Y	Y
Survey weights	Y	Y	Y	Y	Y	Y	Y	Y
Method	Probit	Probit	OLS	OLS	OLS	OLS	OLS	Probit
R-squared	--	--	0.276	0.251	0.660	0.224	0.260	--

Note: Cont DT = continuous DT, I = irrigation access, E = ln(Field experience), C = ln(Capital recovery), S = ln(Seed price), f = ln(Fertilizer price), W = ln(diesel price), and D1 = D1 drought. Convergence issues prevented the inclusion of DT, DT x S, DT x F, and DT x W in the probit regression of DT x I (column 2). To reduce the influence of outliers, prices, experience, capital recovery, and weather deviations have been winsorized. Standard errors have been estimated using the delete-a-group jackknife. Significance is denoted as *** p <0.01, ** p <0.05, * p <0.10.

Table A2. Hedonic Regressions of Per-Acre Corn Seed Prices

	(1)	(2)	(3)	(4)	(5)	(6)
DT, current season	3.367	4.380**	5.413**	5.503**	5.443**	5.721
	(2.291)	(2.201)	(2.260)	(2.324)	(2.458)	(3.640)
GE traits, HT or Bt	25.803***	21.892***	18.974***	18.854***	18.860***	18.826***
	(4.858)	(4.131)	(4.419)	(4.420)	(4.427)	(4.344)
Irrigation access	--	20.132***	20.804***	20.886***	20.644***	20.450***
	--	(3.691)	(3.744)	(3.684)	(3.967)	(3.983)
Ene size, 2nd quartile	--	3.660	3.502	3.485	3.483	2.983
	--	(2.494)	(2.492)	(2.517)	(2.519)	(2.742)
Ent size, 3rd quartile	--	3.551	2.918	2.563	2.567	4.046
	--	(2.505)	(2.461)	(2.442)	(2.443)	(2.651)
Ent size, 4th quartile	--	1.415	0.387	0.452	0.443	0.699
	--	(2.253)	(2.341)	(2.386)	(2.387)	(2.749)
Slope, moderate & uniform	--	4.842***	4.215**	3.932**	3.931**	3.869**
	--	(1.837)	(1.866)	(1.862)	(1.861)	(1.838)
Slope, moderate & variable	--	0.297	1.081	0.747	0.759	0.909
	--	(2.310)	(2.341)	(2.328)	(2.342)	(2.340)
Slope, steep & uniform	--	-0.538	-1.305	-2.143	-2.144	-2.205
	--	(3.660)	(3.480)	(3.961)	(3.964)	(3.846)
Slope, steep & variable	--	-17.396	-17.784	-15.289	-15.297	-15.115
	--	(10.731)	(11.040)	(10.521)	(10.527)	(10.475)
Soil texture, clay	--	-4.528*	-3.920	-4.480	-4.482	-4.591*
	--	(2.612)	(2.742)	(2.729)	(2.729)	(2.731)
Soil texture, sandy	--	-10.799***	-10.471***	-10.957***	-10.950***	-10.925***
	--	(3.775)	(3.876)	(3.857)	(3.859)	(3.829)
Soil texture, mixed or silty	--	-1.999	-1.311	-1.600	-1.609	-1.672
	--	(1.850)	(1.850)	(1.813)	(1.822)	(1.821)
Crop insurance	--	--	1.113	0.845	0.841	0.867
	--	--	(2.585)	(2.693)	(2.698)	(2.749)
Field experience	--	--	1.255	1.247	1.244	1.237
	--	--	(0.998)	(0.977)	(0.980)	(0.981)
Constant	85.841***	74.972***	71.381***	76.264***	76.352***	76.058***
	(9.967)	(8.892)	(10.396)	(9.877)	(9.843)	(9.810)
Obs.	2,576	2,510	2,359	2,359	2,359	2,359
R^2	0.22	0.24	0.24	0.25	0.25	0.25
Year FE	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
State-by-year FE	N	N	N	Y	Y	Y
Drought x irrig	N	N	N	N	Y	Y
Drought x ent size	N	N	N	N	N	Y

Note: Dependent variable is the log of seed prices per acre. Ent = enterprise, drought x irrig = D1 drought x irrigation access, drought x ent size = D1 drought x enterprise size (four quartiles). To reduce the influence of outliers, the field experience variable has been winsorized. Standard errors have been clustered at the county level. Significance is denoted as *** p <0.01, ** p <0.05, * p <0.10.