Climate, Drought Exposure, and Technology Adoption: An Application to Drought-Tolerant Corn in the United States

Jonathan McFadden,[*] David Smith,[†] Steven Wallander[‡]

Abstract

Crop farmers have few short-run options for reducing downside production risk from changes in drought frequency and intensity due to ongoing climate change. However, one recently available option is drought-tolerant (DT) varieties. We determine how recent drought exposure, drought risk, and other climatic features have influenced adoption of DT corn–a water-intensive crop of particular economic importance due to its large share of U.S. agricultural value. Our empirical analysis is motivated by a state-contingent economic framework that accommodates farmers' beliefs about future drought based on objective drought risk and exposure. Using a representative sample of U.S. farmers' fields, we implement a novel econometric method, spatial first differences, that can reduce concerns of omitted variables bias. We find that long-run temperatures and drought risk—rather than short-run drought exposure in recent prior years—led to increased adoption of DT corn varieties in 2016. Farmers are more likely to plant DT corn on highly erodible land and less likely to irrigate such varieties, consistent with the fact that the western Corn Belt was of major marketing focus during the early years of commercialization.

JEL Codes: Q12, Q15, Q16, Q54

Keywords: Climate change, technology adoption, drought tolerance, drought risk, state-contingent modeling, spatial first differences, location fixed effects, irrigation

Acknowledgments: We thank Ryan Williams and Kevin Hunt for assistance with the geocoded data. Ariel Dinar, Gary Libecap, James MacDonald, Roger Claassen, and Seth Wechsler are thanked for their feedback on earlier versions of this research. Seminar participants at USDA-ERS, USDA-FAS, Oklahoma State University, and the University of Oklahoma, as well as participants at the 2018 AAEA conference, 2019 AERE annual meetings, and 2022 NBER conference on "Economic Perspectives on Water Resources, Climate Change, and Agricultural Sustainability" are thanked for comments and useful discussions. The views expressed in this working paper are those of the authors and do not necessarily represent the views or policies of the U.S. Department of Agriculture or the U.S. Environmental Protection Agency.

[*]University of Oklahoma, Department of Economics, jmcfadden@ou.edu.
[†]EPA, National Center for Environmental Economics, smith.david@epa.gov.
[‡]USDA, Economic Research Service, steve.wallander@usda.gov.

1 Introduction

Ongoing climate change is causing complex and potentially irreversible changes to crop growing conditions across the world. In the United States, increases in average temperatures, accompanied by increases in the frequency of warm days and nights, and higher precipitation variability over the central U.S. are amplifying drought risk (Intergovernmental Panel on Climate Change, 2014). Widespread drought prevalence and risk are projected to increase through 2050, with the Rocky Mountain states and the southwestern U.S. experiencing greater drought frequency (Strzepek et al., 2010). These regions, along with the Central Plains, are at high risk of a multi-decadal drought this century (Cook, Ault, and Smerdon, 2015), even as groundwater sources for irrigation in certain areas continue to decline (Steward et al., 2013).

Using historical crop yield data, several applied econometric studies have found little evidence of long-run adaptation to climate change in the production of major U.S. row crops. For example, through a comparison of long difference and panel regression coefficients, Burke and Emerick (2016) conclude that adaptation has offset no more than half of the negative short run impacts of extreme heat on U.S. corn yields. Their median estimate of future climate change impacts suggests that such limited adaptation will contribute to decreases in annual yields by 15% in 2050. Much of this is driven by the finding that corn yields decline sharply at temperatures above 28-29 °C (82.4-84.2 °F) (Schlenker and Roberts, 2009; Burke and Emerick, 2016). However, past agricultural adaptations are imperfectly captured, and the prospects of future adaptation-inducing technical progress (Heisey and Day Rubenstein, 2015) or large-scale price feedbacks (Auffhammer and Schlenker, 2014) cannot be precisely forecasted over long time horizons.

In the short run, crop farmers have few potential tools for reducing downside production risk from changes in drought frequency or intensity. Adoption of irrigation equipment, increased irrigation, or adoption of more efficient equipment are only viable for farmers with access to sufficient irrigation water. Regardless of irrigation availability, no-till crop management and conservation tillage practices can be effective adaptation tools (Powlson et al., 2014) because they reduce soil moisture evaporation and help improve soil water-holding capacity and infiltration. U.S. federal working lands conservation programs, such as the Environmental Quality Incentives Program, pay farmers to use such practices. Federal conservation easement programs like the Conservation Reserve Program can also help certain farmers adapt to drought risk by retiring land from agricultural production (Wallander et al., 2013). Apart from these technologies and management practices, one recent and increasingly-available option is adoption of drought-tolerant (DT) crop varieties.

Non-genetically-engineered (non-GE) DT corn hybrid varieties were commercialized in 2011, while GE DT varieties were released on a limited basis in 2012. Adoption has been rapid in the first five years since introduction: by 2016, just over 22% of U.S. corn acreage was planted to DT varieties (McFadden et al., 2019). Currently, most DT corn acreage is concentrated in drought-prone areas of the western Corn Belt—particularly in Nebraska and Kansas. However, DT corn seed adoption is also significant in the eastern Corn Belt and in regions of relatively lower corn productivity. Climate and drought risk, local growing conditions, and seed company marketing strategies likely factor into farmers' decisions about which corn varieties to grow.

Corn presents a particularly attractive opportunity for studying the economic dimensions of DT crop adoption. First, corn has been a major target of substantial U.S. breeding research into drought tolerance for several decades, culminating in the commercial release of multiple hybrid varieties. Despite the extensive challenges of identifying and manipulating plant genetic material that mediates the plant's complex response to drought, DT varieties have been developed for other crops like soybeans (e.g. Nuccio et al., 2018), though U.S. regulatory approval and commercialization have only occurred very recently, and the full extent of uptake is unknown. Second, corn is a water-intensive crop that is sensitive to high temperatures (e.g. Schlenker and Roberts, 2009), thus making its on-farm management intrinsically interesting—especially within the context of worsening climate conditions. Third, corn is among the most economically important crops in the U.S. Since 2006, annual gross cash receipts for corn have comprised at least 10% of receipts for all U.S. agricultural commodities (U.S. Department of Agriculture, Economic Research Service, 2022), and its share of total annual U.S. planted crop acres has been well over 25% during this same period (U.S. Department of Agriculture, National Agricultural Statistics Service, 2022). Given the sizeable physical and financial value at risk—risk with an increasingly large downside for the U.S. agricultural economy as climate change deepens—an examination of the determinants surrounding this particular drought adaptation tool would seem compelling.

The objective of this study is to determine how drought risk and recent drought exposure impacts the adoption of DT corn in the U.S. We begin by detailing research and development (R&D) of DT corn seeds and the subsequent use of these varieties across the U.S. Next, we motivate our empirical analysis of adoption trends through a state-contingent framework that accommodates farmers' beliefs about future drought based on objective drought risk and exposure. Although nationally-representative microdata of farmers' fields are available, they do not track the same field (or farm operation) over time, which generates concerns of potential bias arising from unobserved heterogeneity. To alleviate this source of potential bias, we implement a new and intuitive econometric method, spatial first differences, which is designed to eliminate time-invariant confounds in cross-sectional regression models.

Our discrete choice analysis suggests that adoption is responsive to long-run drought risk and climate conditions and not the severity or duration of recent droughts. We further find that irrigation reduces the likelihood of adoption, while high erodability increases this likelihood, both of which are consistent with the location-based marketing of these varieties that initially targeted the western Corn Belt.

2 Research, Development, and Uptake of Drought-Tolerant Corn Varieties

Private-sector research on drought tolerance in corn dates back to at least the 1950s (Cooper et al., 2014). Initial research focused on varietal selection for yield performance under drought conditions. Public-sector research began in the mid-1970s (Edmeades, 2012). In contrast to the private sector, non-profit institutions like the International Maize and Wheat Improvement Center (CIMMYT) began selecting for drought tolerance in tropical varieties using an index of traits. The methods (e.g., conventional breeding, molecular breeding, and genetic engineering) and germplasm (i.e., seeds and plants used in crop breeding research) used in both sectors have improved over the past several decades. To date, the international research community has introduced several hundred varieties of DT corn that are adapted to growing conditions in the U.S. and abroad.[1]

By 2012, both non-GE and GE DT corn hybrid varieties had been commercialized in the U.S. Non-GE varieties were developed through the use of molecular breeding, which entailed analysis of field trial data and subsequent selection based on statistical predictions of yield performance and other traits under drought conditions. Non-GE DT corn acreage has increased following its 2011 commercial release (Minford, 2015). By contrast, GE drought tolerance involves insertion of a certain soil bacterium gene into the corn plant's genetic material, which causes expression of a specific protein that helps the plant mitigate drought damages. GE DT corn acreage has also increased since commercialization in 2012 (Castiglioni et al., 2008; Waltz, 2014), but at a slower rate than acreage to corn varieties with conventional drought tolerance (McFadden et al., 2019).[2]

The percent of U.S. corn acreage planted to DT corn varieties increased swiftly in the years following commercialization (fig. 1). In 2012, DT corn (all varieties) accounted for a little over 2% of national corn acreage. By 2016, roughly 22% of U.S. corn acres were drought-tolerant, a 20-percentage-point increase over five years. This growth is similar to that of insect-resistant (Bt) and herbicide-tolerant (HT) corn varieties in their first five years (1996-2000). Comparisons of adoption trends for these three technologies must be interpreted cautiously because each is used to manage different factors that cause yield loss. Bt varieties are mainly used to manage two insect pests common throughout the U.S. Corn Belt. HT traits are used to manage weeds. In contrast, there are several areas of the eastern Corn Belt (e.g., eastern Indiana, Ohio, and western Pennsylvania) where drought is less common. In addition, there was no universal expectation that HT and Bt traits would subsequently

[1] The Drought Tolerant Maize for Africa (DTMA) project (2007-15) was an international partnership that developed and released DT corn varieties adapted for sub-Saharan growing conditions. Wossen et al. (2017) found average yields were 12.6% higher among DTMA DT corn adopters in Nigerian villages under mild droughts than non-adopters. The Water Efficient Maize for Africa (WEMA) project (2013-18) is a public-private partnership that has also developed and commercialized DT corn varieties for certain sub-Saharan nations (Edmeades, 2012). A successor, the Stress Tolerant Maize for Africa project (2016-19), had the goal of developing 70 varieties with more resistance to non-drought stresses, e.g., low soil fertility, diseases, and pests (International Maize and Wheat Improvement Center (CIMMYT), 2018).

[2] As our study relies on data at the initial stage of the DT corn adoption path, it is infeasible to perform an ex post analysis of the returns to drought tolerance R&D for the commercialized varieties.

become "breakthrough" and widely-adopted crop production technologies. Nonetheless, the pace of early DT corn adoption has been comparable to that of other major recent innovations in corn varieties.[3]

Aggregation of national acreage trends masks significant regional variation in 2016 DT corn adoption (fig. 2). Roughly 16-21% of corn in 2016 for the traditional Corn Belt (e.g., Iowa, Illinois, and Indiana) was drought-tolerant, with 14-20% shares of corn acreage in the northern Great Lakes states of Minnesota, Wisconsin, and Michigan. The Great Plains exhibit significant within-state variability, particularly in Nebraska, Kansas, and Texas, though adoption is highest (39-42%) for cropland generally over or near the Ogallala Aquifer. Certain high-latitude regions, like North Dakota, had minimal adoption but also tend to have relatively less corn production.

It is expected that adoption is correlated with incidences of recent and severe droughts (fig. 3). The U.S. Drought Monitor indicates that substantial swaths of the Corn Belt experienced a "severe" (category D2) or worse drought in July 2012. One year later, droughts were concentrated in western states, with many counties in Colorado, Nebraska, Kansas, and Texas experiencing "extreme" (category D3) or "exceptional" (category D4) droughts. These drought patterns are confirmed by spatial variation in July drought risk, as measured by the standard deviation of the Palmer Modified Drought Index (PMDI). Counties that had one or more severe-or-worse droughts in 2011-15 tended to have higher risk. However, most counties in South Dakota, North Dakota, and Minnesota did not experience significant drought over 2011-15, despite being higher-risk. Conversely, many Texas counties experienced more frequent and/or more severe droughts during 2011-14 than might be implied by their long-run risk. These discrepancies in short-run exposure and long-run risk partially motivate our economic framework, which we discuss next.

[3]It should be noted that these traits are often bundled in the same variety. For example, 54% of corn fields in our sample were planted to varieties with HT and Bt traits, while 20% were planted to varieties with DT, HT, and Bt traits. Despite such bundling, it does not appear that climate, drought risk, and other regressors of interest have larger effects on adoption of HT or Bt corn than DT corn. This conclusion is supported by complementary multivariate econometric analysis, which we exclude here for space considerations (estimates available upon request).

3 Economic Framework

We define the farmer's state-contingent and partial (drought and drought-abating) per-acre profit (π) function as

$$\pi_s = PY_s\left(\boldsymbol{X^D}, \boldsymbol{X^D_s}\right) - \boldsymbol{P^X}\boldsymbol{X^D} - \boldsymbol{P^{X_s}}\boldsymbol{X^D_s}, \tag{1}$$

where P is the output price[4], Y_s is yield, $\boldsymbol{X^D}$ is a vector of state-independent drought-abating inputs, $\boldsymbol{X^D_s}$ is a vector of state-contingent drought-abating inputs, $\boldsymbol{P^X}$ is a vector of prices for these inputs and s is an index for a state of the world.

We assume that yields are a multiplicative function of drought-free yields (Υ) and a drought abatement function ($d_s(.) \in \{0, 1\}$), defined over the unit interval. The drought abatement function is the percentage of the drought-free yields that are not damaged by the drought,

$$Y_s = \Upsilon d_s\left(\boldsymbol{X^D}, \boldsymbol{X^D_s}; D_s, \boldsymbol{I}\right). \tag{2}$$

The drought abatement function is dependent on drought damage (D_s), drought abatement ($\boldsymbol{X^D}, \boldsymbol{X^D_s}$) and the ability to irrigate ($\boldsymbol{I}$). In this framework, $\boldsymbol{I}$ is a set of exogenous parameters indicating: 1) whether irrigation equipment has been previously installed on a field, and 2) whether irrigation water is available. This reflects the idea that, within a single growing season, farmers cannot choose whether their fields are irrigable or if water is available. In other words, farmers must make their drought abatement choices contingent on the capacity to irrigate.[5] When there is no drought or if the inputs fully abate damages from drought then $d_s = 1$ and yields are equivalent to drought-free yields. If the drought is devestating, then $d_s = 0$ and the crop is lost ($Y_s = 0$).

The drought-abating inputs can be separated into a vector of inputs contingent on drought $\boldsymbol{X^D_s}$ and inputs that are not contingent on drought $\boldsymbol{X^D}$. Importantly, seed decisions occur well before planting, and thus drought-tolerant (DT) seed use is not state-contingent (i.e., farmers must make this decision before observing the state of drought during the grow-

[4]We assume that farmers consider output and input prices not to be state-contingent.

[5]To economize on notation in the remaining exposition, we do not explicitly index farmers' optimal choices by these irrigation parameters.

ing season). Other examples of state-independent drought-abating inputs are adjustments to planting dates, row spacing, seeding rates, and the installation or upgrade of irrigation equipment. These also include conservation practices that have long-term effects on soil organic matter and water-holding capacity, such as conservation tillage and cover crops. The set of state-contingent drought-abating inputs is somewhat limited but include increases in irrigation application rates, changes in late season herbicide use to reduce competition from weeds for water, and reductions in fertilizer applications to reduce water demand.

The farmer's objective is to maximize state-contingent profits, choosing whether or not to use drought-abating inputs

$$\max_{\boldsymbol{X^D},\boldsymbol{X_s^D}} W\left(\boldsymbol{\pi}\right), \tag{3}$$

where $W : R^s \mapsto R$ is a non-decreasing continuous function of a profit vector ($\boldsymbol{\pi} = \pi_1, \pi_2, ..., \pi_s$) indexed by state $s \in S$. Farmers will choose to use a drought-abating input if

$$W\left(\boldsymbol{\pi^1}\right) > W\left(\boldsymbol{\pi^0}\right), \tag{4}$$

where $\boldsymbol{\pi^1} = \boldsymbol{\pi}\left(x^D = 1|\boldsymbol{X^D}, \boldsymbol{X_s^D}; \boldsymbol{I}\right)$ and $\boldsymbol{\pi^0} = \boldsymbol{\pi}\left(x^D = 0|\boldsymbol{X^D}, \boldsymbol{X_s^D}; \boldsymbol{I}\right)$.

A number of preference functions, $W : \Pi^s \mapsto R$, defined on the set of profit outcomes, Π with elements, π_s , have been used in the economics literature on choice under risk and uncertainty. We present two commonly-used preference functions to motivate our empirical models. Such preferences give rise to empirical specifications suggesting that short-run drought shocks and long-run drought risk can influence farmers' economic decision making. Given that farmers' underlying preference structures are unknown and difficult to determine empirically, we estimate separate regression models.[6]

[6] In earlier versions of this research that used drought severity indicators, we estimated the structural regression models implied by the below derivations. We found many of the structural parameters were individually significant and implied marginal effects similar to those from reduced-form weighted probit regressions of adoption on the drought severity indicators.

3.1 Mean-Variance Utility

The objective of a risk-facing farmer with risk-neutral preferences is simply to maximize expected profits. However, some empirical agricultural production models have shown utility-maximization models provide better fit than expected profit maximization (e.g. Lin, Dean, and Moore, 1974). We choose the mean variance model with preference function

$$W(\boldsymbol{\pi}) = v\left(\mu(\boldsymbol{\pi}), \sigma^2(\boldsymbol{\pi})\right). \tag{5}$$

Note that $v : (\mu, \sigma^2) \mapsto R$ is a utility function, $\mu[\boldsymbol{\pi}] = \sum_{s=1}^{S} \rho_s \pi_s$, where π_s occurs with probability ρ_s and $\sigma^2[\boldsymbol{\pi}] = \sum_{s=1}^{S}{}_s \left(\pi_s - \sum_{s=1}^{S} \rho_s \pi_s\right)^2$. Substituting in the production function, $Y_s = \Upsilon d_s$, we can then choose a preference function such that

$$v^1 - v^0 = P\Upsilon \exp\left\{\mu[\pi_s^1(d_s)] - \mu[\pi_s^0(d_s)] - \left(\sigma[\pi_s^1(d_s)] - \sigma[\pi_s^0(d_s)]\right)\right\} - p^x. \tag{6}$$

The preference function defines the marginal utility of drought abatement.[7] With this preference function, a farmer will choose to use drought abating inputs if $v^1 - v^0 > 0$, i.e., if her utility from adopting these inputs exceeds her utility from not adopting them. Re-arranging this inequality and applying the logarithmic transformation implies that

$$\ln P + \ln \Upsilon + \mu[\pi_s^1(d_s)] - \mu[\pi_s^0(d_s)] - \left(\sigma[\pi_s^1(d_s)] - \sigma[\pi_s^0(d_s)]\right) > \ln p^x. \tag{7}$$

If the mean of utility (of profits) from adopting drought-abating inputs relative to the utility from not adopting is approximately zero, i.e. $\mu[\pi^1(d_s)] \approx \mu[\pi^0(d_s)]$, which would be expected to occur in long-run equilibrium, then (7) leads directly to an estimating equation once an operationalized measure of long-run drought risk is assumed. Using the standard deviation of the Palmer Modified Drought Index (PMDI) as our measure of drought risk, we can estimate

$$\beta_0 + \beta_\Upsilon \ln \Upsilon + \beta \sigma_{PMDI} > \epsilon, \tag{8}$$

[7] The preference function is increasing in output prices, drought free-yields, and mean drought abatement. The marginal utility of drought abatement is decreasing in the variance of drought abatement. As Chambers and Quiggin (2000) note, the variance can be replaced by any index for riskiness. Without loss of generality, we replace the variance with the standard deviation.

where β_0 subsumes prices, β captures the effects of variability in profits from adopting drought-abating inputs relative to the variability in profits from not adopting drought-abating inputs, as underlying functions of drought (conceptualized here as states), and ϵ is an econometric error term.

3.2 Prospect Theory

Mean-variance models and other expected utility models have theoretical shortcomings and do not always reconcile with empirical evidence (e.g. Schoemaker, 1982). For example, individuals often over-weight low probability states and under-weight high probability states (e.g. Kahneman and Tversky, 1979). This can have important implications for farmers' decisions to use drought-abating inputs. In some regions, severe or extreme drought is rare, but if some farmers attach substantial importance to these rare but damaging occurrences, their adoption rates could be systematically higher than expected assuming that farmers did not over-weight such events.[8] For these reasons, we also use the following preference function

$$W(\boldsymbol{\pi}) = \sum_{s=1}^{S} h(\rho_s) u(\pi_s), \tag{9}$$

where $h(.)$ is a probability weight function, and $u(.)$ is a utility function. Note this model assumes farmers know the probability of each possible state and systematically weight these probabilities. This model can be simplified by assuming that the marginal rate of substitution between two state-dependent profits is $MRS_{ss'} = \frac{u\left(\pi_s^1\right) - u\left(\pi_s^0\right)}{u\left(\pi_{s'}^1\right) - u\left(\pi_{s'}^0\right)} = \frac{w_s\left(\pi_s^1 - \pi_s^0\right)}{w_{s'}\left(\pi_{s'}^1 - \pi_{s'}^0\right)}$, where w_s is the preference weight a farmer assigns to profits in each state. The probability-weighted marginal utility of drought abating inputs is $\omega_s\left(\pi_s^1 - \pi_s^0\right) = h(\rho_s) w_s \left(\pi_s^1 - \pi_s^0\right)$, where ω_s is a weight that combines the probability and preference weights. Farmers will adopt drought-abating inputs if

$$\sum_{s=1}^{S} \omega_s \left(\pi_s^1 - \pi_s^0\right) > 0. \tag{10}$$

[8] Similarly, if the frequency, duration, and severity of droughts are expected to increase under unmitigated climate change, then adoption rates for those who systematically under-weight such events may be lower, even as the objective probability of such occurrences increases over time.

Substituting in the production function, $Y_s = \Upsilon d_s$, farmers will adopt if

$$P\Upsilon \sum_{s=1}^{S} \omega_s \left(d_s^1 - d_s^0\right) > p^x, \tag{11}$$

where $d_s^1 \in (0,1)$ is the percent of yields not damaged by drought when using a drought-abating input, and $d_s^0 \in (0,1)$ is the percent of yields not damaged by drought when not using a drought-abating input. We do not observe farmers' preference weights on state-dependent outcomes and probabilities when making their abatement decisions. A common approach is thus to use the historically-observed states to proxy for the states that farmers face when making such decisions. Here, we assume that farmers use their experience of realized states from previous years to form their set of possible states. States can be defined according to the drought severity categories from the U.S. Drought Monitor, for example, such that

$$P\Upsilon \sum_{s=1}^{S} \sum_{t=1}^{T} \omega_s \left(d_s^1 - d_s^0\right) D_{st} > p^x, \tag{12}$$

where D_{st} is an indicator for drought in state s and year t. Assume that drought-related yield losses are reduced according to the function, $\exp\left(\sum_{s=1}^{S} \sum_{t=1}^{T} \omega_s \left(d_s^1 - d_s^0\right) D_{st}\right)$.[9] Substituting this into (12) and applying a logarithmic transformation, we get the following inequality

$$\ln P + \ln \Upsilon + \sum_{s=1}^{S} \sum_{t=1}^{T} \omega_s \left(d_s^1 - d_s^0\right) D_{st} - \ln p^x > 0. \tag{13}$$

This leads to an empirical equation that resembles

$$\alpha_0 + \alpha_\Upsilon \ln \Upsilon + \sum_{s=1}^{S} \sum_{t=1}^{T} \alpha_{st} D_{st} > \epsilon. \tag{14}$$

[9] If there is no drought in any state ($D_{st} = 0$), then yields in all states are drought free (i.e., $Y_s = \Upsilon$).

4 Empirical Strategy: Identification and Data

The motivating economic framework suggested that producers could consider short-run shocks and/or long-run risk when making drought abatement adoption decisions.[10] However, owing to the standard *ceteris paribus* assumption in regression models, it would not be suitable to include both measures in the same specification. This is because long-run drought risk will not be plausibly constant if drought frequency, duration, and severity change annually during a half-decade period.[11] We therefore estimate separate specifications.

Using weighted linear probability (LPM) regressions, we first estimate the "mean-variance empirical model" of DT corn variety adoption on field i in year 2016 as

$$DT_i = \beta_0 + \beta_{DR}\sigma_{PMDI,i} + \beta_{\overline{W}}\overline{W}_i + \beta_{Irr}Irr_i + \beta_{SL}SL_i + \epsilon_i, \tag{15}$$

where DT_i is an indicator of DT seed variety adoption; $\sigma_{PMDI,i}$ is the standard deviation of the PMDI measure in July for field i in 2016; $\overline{W}_i$ is a vector of average temperature and precipitation conditions, and their standard deviations, over the 30 previous years (as a proxy for climate); Irr_i is a vector of variables denoting field irrigation capacity and their interaction terms; and SL_i is a vector of field-level soil characteristics, land attributes, and corn basis from nearby grain elevators for February 2016. Note that $\sigma_{PMDI,i}$ is a normalized measure of variability in natural soil moisture over the past century (Wallander et al., 2013). For purposes of model assessment, we compare estimated coefficients to average marginal effects from corresponding weighted probit regressions.[12]

Similarly, we estimate the following "prospect-theoretic empirical model" of DT corn variety adoption using weighted LPM regressions

$$DT_i = \alpha_0 + f(\alpha_{st}, D_{st,i}) + \alpha_{\overline{W}}\overline{W}_i + \alpha_{Irr}Irr_i + \alpha_{SL}SL_i + \epsilon_i, \tag{16}$$

[10] Farmers may also consider short-run or seasonal climate forecasts when making agricultural decisions. Appendix B in the Supplementary Information contains a discussion of this point.

[11] In contrast, it is plausible to hold long-run drought risk constant while varying the first two moments of long-run average temperature and precipitation (and vice versa), which is done in our empirical application.

[12] Under the assumptions of the linear probability model for binary response variables, the ordinary least squares (OLS) estimates of the coefficients are unbiased and consistent. Moreover, the LPM may be preferred to standard probit models when there are several discrete covariates, each with a limited number of values (Wooldridge, 2010).

where $f(\alpha_{st}, D_{st,i})$ is a simple linear function of drought incidence with severity s in year t.[13] We do not use drought severity indicators as suggested by our motivating framework because of multicollinearity concerns. Rather, we make use of two variables designed to capture the duration and severity of farmers' recently-experienced droughts: 1) the total number of months of severe, extreme, or exceptional droughts during years 2011-2015, and 2) the most intense drought experienced during the growing season (May-September) throughout 2011-2015.

4.1 Identification and Causal Impacts of Climate in Cross-Sectional Regressions

Over the past two decades, a surge in the number of empirical studies relating weather and climate to economic outcomes has brought methodological improvements in econometric applications. For agricultural outcomes, some studies have analyzed cross-sectional data (e.g. Mendelsohn, Nordhaus, and Shaw, 1994), while others make use of panel data (e.g. Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009) or long [temporal] differences (Burke and Emerick, 2016). Under certain conditions, Hsiang (2016) shows that, locally, the marginal effect of climate is equivalent to the marginal effect of weather in linear regression models estimated on data with repeat observations over time.

Credible identification of climate effects in cross-sectional analyses is particularly challenging because of omitted variables bias. Unmodeled factors that are correlated with outcomes (e.g., adoption of seed technologies, crop yields, farmland values, revenues) and one or more covariates will produce biased estimates. For example, cross-sectional regressions of farmland values on temperatures that omit irrigation access will have biased estimates because irrigation access is capitalized into valuation of farmland and is positively correlated with temperature (Schlenker, Hanemann, and A. Fisher, 2005). Generally, climate is not random over large areas. In our application, there are several unmodeled, time-invariant

[13] Farmer demographics, like education, as well as other dimensions that are more difficult to measure (e.g., risk preferences, broader human capital) are also expected to influence adoption (e.g. Wozniak, 1987). We can link our surveyed fields to their operators using data from the 2016 ARMS Phase III, but the benchmark sample size declines by roughly 40%. However, our estimates of the impacts of long-run drought risk change only minimally after controlling for years of farming experience, indicators for education level (high school diploma, some college, and four-year college degree), and gender.

factors correlated with climate and DT variety adoption that could confound identification of causal impacts: (i) input dealer recommendations, (ii) agricultural cooperative guidelines, (iii) ethanol plant contract terms, (iv) university extension guidance, (v) local USDA office practices, and (vi) other location institutions that could induce correlations in farmers' behavior over short distances.

One potential solution is to saturate the regression model with as many economically-relevant covariates as possible. However, it is impossible to know if all important variables have been included; further, saturation can lead to overfitting and high standard errors in models with severe multicollinearity. For some economic outcomes (including many in agriculture), accumulated evidence from a variety of studies can provide useful guidance on whether or not important covariates have been excluded (Hsiang, 2016).

Spatial first differences (SFD) have been proposed as a method for reducing concerns of omitted variables bias (Druckenmiller and Hsiang, 2018). The framework rests on a fundamental premise of spatial statistics: observations closer together are more similar than those farther apart from one another. That is, the presence of unobserved location effects, c_i, may drive most or all of the similarities among observations at short distances. As such, the SFD estimator results from an OLS regression of differenced outcomes (y_i) on differenced covariates x_i between spatially-adjacent observations i and $i-1$:

$$y_i - y_{i-1} = (x_i - x_{i-1})\beta + (c_i - c_{i-1}) + (\epsilon_i - \epsilon_{i-1}), \tag{17}$$

where ϵ is a mean-zero i.i.d error term, β is a vector of parameters, and α is a vector that measures the influence of fixed effects.

Identification in the SFD framework rests on a Local Conditional Independence Assumption: $E[y_i|x_{i-1}] = E[y_{i-1}|x_{i-1}]$ for all {i,i-1}, i.e., the expected outcome is the same for two neighbors if they receive the same treatment. This identification condition is nearly equivalent to that assumed to hold in first-differenced time series models and is similar to those for certain differences-in-differences panel estimators and regression discontinuity designs. Importantly, the Local Conditional Independence Assumption is weaker than the Conditional Independence Assumption underlying a cross-sectional regression in which spatial fixed effects have been omitted: $E[y_i|x_j] = E[y_j|x_j]$ for all $i \neq j$, i.e., distant units are comparable in that the same expected outcome would result if both observations were treated with x_j—even though only j received x_j. In practice, the SFD model eliminates spatially-correlated unobserved heterogeneity by filtering out the influence of factors that vary at short distances (not immediately adjacent observations) and differencing out common idiosyncratic influences at adjacent observations (Druckenmiller and Hsiang, 2018).

To control for potentially important location fixed effects that cannot be estimated in the cross-sectional analysis, we re-estimate LPM versions of (15) and (16) using differenced data on DT corn seed variety adoption and differenced data for all covariates. Distinct from the application in Druckenmiller and Hsiang (2018), which differences county crop yields and covariates in the north-south direction (and then analyzes to what extent results are robust to differencing in the east-west direction), we define spatially-adjacent fields to be fields that are closest to each other, regardless of direction. This assumes that the angle between neighboring fields is unimportant, which is plausible for our measures of adoption, weather, and climate.[14] In particular, adoption of drought-tolerant seed varieties appears to be spatially correlated, though there are not pronounced spatial effects in any cardinal direction (fig. 4).

4.2 Data: Field-level Agricultural Production and Gridded Weather-Climate Observations

The Agricultural Resource Management Survey (ARMS) is our primary source of data.[15] ARMS is a survey conducted each year on farms' production practices (e.g., crop choice and rotations, tillage operations, conservation program enrollment and assistance), input use (e.g., GE trait choices, chemical applications, and irrigation use), soil and land characteristics, farm business and household financial characteristics, and operator household demographics (U.S. Department of Agriculture, Economic Research Service, 2016). We use data from Phase II of the 2016 ARMS, which randomly-sampled one corn field per farm in

[14]To our knowledge, neither drought incidence (fig. 3) nor seed adoption (fig. 4) fall along strict geometric patterns. Although major precipitation events captured in our sample generally moved west-east, this directional component would be less important for our 30-year weather average calculations.

[15]Appendix A in the Supplementary Information contains an overview of the data used in this analysis.

the survey.

The year 2016 is the first year in which ARMS Phase II surveyed farmers about their use of DT corn seeds, for both the 2015 and 2016 seasons. Using a 'base' weight provided by USDA's National Agricultural Statistics Service (NASS), our sample expands to 73.3 million corn acres, representing just over 78% of 2016 U.S. corn acreage (U.S. Department of Agriculture, National Agricultural Statistics Service, 2018b). Roughly 20% of 2016 sample corn acres were planted with DT varieties (table 1), similar to the national average of 22% (McFadden et al., 2019).

We merge drought-related weather and climate data with the ARMS data for the regression analysis. The U.S. Drought Monitor produces expert-adjusted observational data through a collaboration of USDA, the National Drought Mitigation Center at the University of Nebraska-Lincoln, and the National Oceanic and Atmospheric Administration (NOAA).[16] The main benefits of the U.S. Drought Monitor are that it provides: (i) drought categories that are easy to interpret, and (ii) policy relevance.[17] However, the U.S. Drought Monitor is subject to expert review and revision, which could introduce noise and reduce comparability across locations. We therefore base our classifications of severe, extreme, and exceptional droughts (the Drought Monitor's severity classes) on values of the PMDI, also produced by NOAA.[18] To construct field-level values of the drought measures, we interpolated PMDI data at the 12 nearest stations within 100 miles of sample fields (within the continental U.S.) using inverse distance weighting. This assigns more weight to stations closer to our sample fields than more distant stations.

The PMDI itself is an "operational" version of the Palmer Drought Severity Index (PDSI),

[16]In order to produce drought estimates, the U.S. Drought Monitor first relies on data from other drought and precipitation indices; fire risk data; satellite imagery of vegetation health; soil moisture data and model estimates; and hydrologic data. These are synthesized to develop an initial weekly assessment of the percent area of each county that is in one or more of five drought categories, including an "abnormally dry" category. This initial assessment is sent to over 350 observers across the U.S. These observers include meteorologists, climatologists, hydrologists, and extension agents whose weather expertise and knowledge of local conditions inform their reports of drought impact. The initial assessment is subsequently revised to incorporate these experts' collective judgment(U.S. Drought Monitor, 2019).

[17]USDA uses the U.S. Drought Monitor as a guide to making disaster declarations and to help determine eligibility for certain types of loans. The index is also used by USDA's Farm Service Agency to help determine eligibility for the Livestock Forage Program. This program compensates eligible livestock producers for certain grazing losses, including losses resulting from qualifying drought conditions.

[18]PMDI values are mapped into Drought Monitor severity categories as follows: -1.0 to -1.99 (D0), -2.0 to -2.99 (D1), -3.0 to -3.99 (D2), -4.0 to -4.99 (D3), and -5.0 to -5.99 (D4) (U.S. Drought Monitor, 2019).

which quantifies the duration and intensity of long-term drought patterns. The PMDI uses hydrologic models to estimate net soil moisture based on precipitation recharge and losses from evapotranspiration, infiltration, and runoff. The PMDI introduced the concepts of severe, moderate, and extreme drought based on PDSI values (Heddinghaus and Sabol, 1991; Wallander et al., 2013). The fields in our sample experienced abnormally dry conditions (D0) much more frequently than droughts across all years. However, nearly two-thirds of fields experienced a severe or extreme drought at some point in 2012. More broadly, the 2012 drought affected two-thirds of all land in the U.S., causing agricultural losses estimated at $30 billion (Rippey, 2015). By contrast, the 2013 drought was mainly severe for fields located in western counties. On average, fields experienced roughly 4-5 months of severe-or-worse droughts, in total, across the corn growing seasons of 2011-15. Similarly, many of the fields were at risk of experiencing a drought of any severity in any given year; the weighted mean of the standard deviation of long-run PMDI was 2.26 (table 1).

Yearly temperature and precipitation are taken from Oregon State University's PRISM Climate Group, from which we construct 30-year averages. The PRISM data uses point observations, a digital elevation model, and other spatial datasets to generate estimates of climatic parameters (e.g., temperature and precipitation) at 4 km x 4 km grids (Daly, Neilson, and Phillips, 1994). For each of the 4 km grids, we aggregate to the county based on distance to county centroids, clipped and weighted by cropland density. To avoid the possibility that 2015 weather averages might correlate with our measures of drought, drought risk, and other idiosyncratic effects in 2015, we calculate yearly averages from monthly observations between 1985 and 2014. Only months in the corn growing season were used. Nationally, the average 30-year growing season temperature was 20.5 °C (69 °F), with mean precipitation of 4.1 inches (table 1).

Our ARMS-based field-level measure of one aspect of irrigation capacity, whether the field is irrigable, is a variable indicating if the corn crop was irrigated in that year. Only six percent of corn acres in our sample are irrigated, consistent with the fact that the vast majority of DT corn was grown on non-irrigated cropland in 2016, even among states that are major corn irrigators (McFadden et al., 2019). Our second measure of irrigation capacity is irrigation water availability, though we must proxy for this in the absence of spatiallydetailed, representative data on surface water and groundwater availability. We represent this as the share of each county's harvested corn acreage that was not irrigated, using data from the 2012 Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistics Service, 2013). We expect large shares of non-irrigated acreage to signal a general lack of water availability, but because availability only matters for irrigable fields, we prefer to include the [irrigable × water availability] interaction term and omit the proxy in levels. Nationally, approximately 86% of harvested corn acreage in 2012 was not irrigated.

We also take certain field-level indicators of soil type and quality from the ARMS data. Roughly 15% of the sample acreage had a primarily clay soil type. Given that clay soils are better at retaining water than other soil types, we might expect lower DT corn adoption under adequate soil moisture. Further, the effect of soil type on DT corn adoption may depend on both measures of irrigation capacity, and so we include both interaction terms, [irrigable × clay] and [irrigable × water availability × clay]. In contrast, adoption on highly-erodible soils might be higher due to a combination of steeper slopes and greater potential for soil detachment, which can contribute to soil moisture loss. Roughly 17% of sample acres are highly erodible.

We control for other unobserved countywide land productivity attributes through use of USDA's National Commodity Crop Productive Index (NCCPI) for corn and soybeans (Dobos, Sinclair, and Robotham, 2012). After re-scaling, these index values lie in [0,10], with higher values indicating higher inherent soil suitability for growing corn and soybeans.[19] The NCCPI values are available at the geographic level of a "map unit" polygon, of which there are several thousand per U.S. state. These polygon values are then aggregated to 30 m cells as part of USDA's Gridded Soil Survey Geographic Database (U.S. Department of Agriculture, Natural Resources Conservation Service, 2018). Our corn-soy soil productivity index is created by averaging over values of NCCPI for all 30 m cells within 3 km of each field's location. As expected, most fields are suitable for growing corn, with an average county value of 6.01, though there is significant variation in soil quality within our sample.

[19] USDA calculates this index as the product of ratings from five input category subrules: chemical (e.g., soil pH, cation exchange capacity, organic matter), water (e.g., available water-holding capacity, precipitation during the growing season), physical (e.g., saturated hydraulic conductivity, rock fragments), climate (e.g., frost-free days, total precipitation), and landscape (e.g., slope gradient). Interested readers should consult Dobos, Sinclair, and Robotham (2012) for more information.

National seed premiums for DT corn variety traits were roughly $10 per bag of 80,000 seeds in 2016 (McFadden et al., 2019). Although some evidence suggests that DT seed premiums are lower in eastern states, where drought is less common, farm- or state-level data for DT corn premiums are not widely available (Farmers Business Network, 2018). To proxy for the price of corn, we use a field-matched measure of basis, which can be thought of as a location-adjusted net corn price (Barr et al., 2011). In particular, we subtract the February 2016 cash price from the March futures price for the December contract. February is chosen as this is the time operators of most U.S. corn acreage make choices of seed varieties to plant. We assign cash spot prices to the nearest ARMS fields using USDA-collected cash grain bids data.[20] The weighted average basis in our sample is -$0.15.

5 The Role of Drought Exposure and Climate on Adoption of Drought-Tolerant Corn Varieties

We first discuss the LPM regression results for the models motivated by both behavioral assumptions and compare them with benchmark probit results. Next, we examine the extent of spatial variation in the data and the effects of controlling for potentially-confounding locality factors through SFD estimation. Last, we provide an illustrative discussion of the role of climate change attitudes, beliefs, and potential barriers to adoption.

5.1 Benchmark Adoption Estimates

We find that long-run drought risk is positively associated with farmers' adoption of DT varieties, consistent with expectations and evidence about the geographic regions in which these technologies were first introduced (table 2, column 1a). Controlling for climate effects, a one-standard-deviation increase in 100-year drought risk leads to increased adoption by

[20] We first removed outliers from the basis data and then fit an inverse distance weighted surface to the remaining points. We looked for the nearest five purchasers (e.g., grain elevators) within a maximum of 70 miles from the field. This is generally the greatest distance growers will truck grain. Roughly 97% of fields were within 70 miles of one or more grain purchasers. Among these fields, only 146 had fewer than five purchasers within the 70-mile radius. The average distance to a purchaser was just over 16 miles.

10.6 percentage points, a large but insignificant effect.[21] Thus, long-run drought risk does not appear to have significant predictive content after controlling for 30-year temperature and precipitation means and standard deviations. However, an additional 1 °C increase in average climate conditions increases adoption by 2.4 percentage points. Operators of fields that are of inherently lower productivity—those that are highly erodible —are more likely to have planted DT varieties.

Irrigation has an insignificant main-level effect with the expected negative sign, though its impact varies by soil type. Specifically, the effect of irrigation on adoption is roughly 66 percentage points higher on fields with primarily clay soils located in areas with very high shares of irrigated acreage. But as irrigation water becomes incrementally less available (as proxied by a marginal increase in the county's share of irrigated acreage), DT corn adoption on irrigable fields is higher for non-clay fields but lower for clay fields. However, both interaction terms involving the water availability proxy are insignificant.

The LPM results are robust to the exclusion of the climate controls (table 2, column 2a) with few exceptions. The marginal effect of long-run drought risk nearly doubles to 0.197 and becomes significant at the 5% significance level, absorbing much of the influence of the excluded moments of the 30-year weather distribution. Somewhat surprisingly, February basis (our output price control) becomes significant at the 5% level. This suggests a degree of collinearity between basis and our gridded climate data.

Our set of results are also robust to dropping the long-run drought risk index entirely (column 3a), though the quality of fit somewhat changes. The 30-year temperature average and precipitation variability increase the probability of adoption, with the latter having a large 13.8-percentage-point effect. That average precipitation remains insignificant (though with the expected sign) echoes a major finding in the climate econometrics literature on crop yields: average precipitation effects are relatively small and variable (e.g. Schlenker and Roberts, 2009; Burke and Emerick, 2016). One distinction, however, is that our study relies on drought exposure, climate, and adoption data at a finer spatial scale than the county.

As expected, the average marginal effects from the probit model (columns 1b-3b) are

[21] For our sample, this would be roughly similar to an area with moderate drought risk becoming an area with severe drought risk.

very similar to the partial effects identified in the LPM regressions. Differences between the two sets of estimates imply differences in impacts on adoption rates that are less than 1 percentage point, on average. Given that our focus is on identification of drought exposure and climate effects, rather than out-of-sample prediction, it is of less importance if predicted probabilities from the LPM regressions lie outside [0,1], although this did not occur for any of the regression specifications.

The duration and severity of recent droughts do not appear to affect seed technology adoption (table 3). Although the total duration (in months) of severe, extreme, or exceptional droughts has the expected sign, its magnitude is near zero and insignificant. Similarly, the severity variable suggests that adoption is roughly 2 percentage points higher as the five-year maximal PMDI increases by one index value (columns 2a and 2b), though these estimates are also insignificant. The switch in signs on this variable between the "drought shocks & climate" regressions relative to the "shocks only" regressions is suggestive of substantial collinearity with the temperature and precipitation climate variables. Though to some extent surprising, this null result is in agreement with other work suggesting climatic effects of temperature and rainfall explain most of the variation in corn yields, though with some remaining effects due to drought (e.g. Kuwayama et al., 2019).

Consistent with expectations, increased average temperatures and variability of rainfall lead to higher adoption, though the latter is statistically insignificant. Similarly, adoption rates are higher on highly erodible land. As with the estimates in table (2), irrigation leads to lower adoption, with point estimates that are comparable but roughly 1-2 percentage points lower and again insignificant. Irrigation effects are also moderated by the dominance of clay in the topsoil profile, though interactions with the proxy for water availability remain insignificant.

5.2 Spatial Differences Estimates: Controlling for Unobserved Location-Specific Heterogeneity

As a precursor to SFD estimation, we first examine variation in the differenced data (table 4). We choose thresholds corresponding to the 75th percentile (14 miles), 50th percentile (9 miles), and 25th percentile (6 miles) of the distribution of distance between fields. Since we are differencing data for each field from those at the next closest field, many of the means are zero or close to zero.[22] There is no broadly meaningful interpretation of small positive or negative means because of this spatial, rather than temporal, differencing.

Relative to their means, many of the differenced drought and climate data have large standard deviations. Across the three distance quartiles, the range of the absolute value of the coefficient of variation (CV) for the drought duration measure is [49, 142], with a similar CV range for the intensity measure: [31, 182]. Variability in the 30-year climate regressors is somewhat lower. Clay content and the indicator of high erodibility have comparatively large variation, as expected, while the interaction terms, corn-soy soil productivity index, and basis have among the least variation in the differenced data.

We also computed correlation coefficients for each covariate for observations matched with its closest other observation. If we observe relatively high correlations in all of the covariates of interest at close distances, this could suggest (but does not prove) that location fixed effects—if uncontrolled for—could bias estimation in levels. However, even if such effects are absent, spatially differencing the data may help to reduce codependence among fields in our data. Consistent with the summary statistics in table 4, many of the weather and climate measures are highly correlated, even when the nearest-neighbor field is roughly 15 miles away. At this distance threshold, correlations in drought risk and 30-year temperature averages are in excess of 0.97, and this correlation increases to over 0.99 for fields located to their closest other fields less than five miles away. A similar pattern holds for basis. For these reasons, we do not estimate the SFD model with these highly-spatially-dependent data.

There is significant variation in distances between our sample points (fig. 5), and there are few fields whose nearest field exceeds 30 miles, generally the average north-south distance of major U.S. corn growing counties (Druckenmiller and Hsiang, 2018). The differencing process results in samples that get increasingly smaller (925, 613, and 356 fields), with an accompanying decline in the models' degrees of freedom. For purposes of comparison, we

[22] With first-differenced time series data, a single observation in levels generally appears in differencing calculation exactly *twice* (e.g., subtract year 2014 from year 2015, subtract year 2015 from year 2016). There are 30 fields in our levels dataset that are used more than twice to construct the differenced data (e.g., for fields A, B, and C, the closest field is Field D). Our results are robust to their exclusion.

estimate the same model in level terms, adding back in the climate and price variables that were removed in the SFD estimation, for the samples that would have resulted had we not spatially differenced (with comparable sample sizes). As in the LPM and probit results, all standard errors have been clustered at the level of USDA's crop reporting districts.[23]

For the SFD model estimated at the 14-mile distance, the drought-specific variables are again insignificant (table 5, columns 1a and 1b). At this distance, it is unclear whether or not the location effects have been completely differenced out, while the model is estimated with fewer observations—and that exhibit less variation. Regarding other attributes, irrigation and its interaction with clay are significant, while the presence of highly erodible land are is insignificant. The corn-soy soil productivity index is now significant at the 5% level and suggests that, relative to fields which are completely unsuitable for growing corn, DT varieties are adopted at rates 77 percentage points higher among fields that are deemed to have the highest suitability for corn.

Several of the estimated coefficients in the SFD model for the dataset at the 9-mile threshold (2a) are qualitative similar to those obtained in the 14-mile sample (1a), as well as level estimates at the 9-mile threshold (2b). The drought duration variable remains small and insignificant, although the drought intensity variable is now marginally significant. There is broad consistency in the signs and sizes of the soil coefficients between (1a) and (2a), though the larger effect of the irrigation-clay interaction term is more precisely estimated in (2a). Less variation in the corn-soy soil productivity index at smaller distances contributes to the smaller coefficient estimate and insignificance.

Many of the SFD point estimates for fields with neighboring observations that are at a distance of 6 miles or less (3a) are similar to counterparts at greater distances. By differencing out potentially bias-inducing spatial fixed effects, the impacts of the weather and climate effects are magnified, especially as seen in (3b). The restricted sample size is also contributing to some of the increase in magnitude of these estimates. Given the novelty of the spatial first differences approach, the consequences of restricting samples to observations that could be

[23]Crop reporting districts (CRDs) are groupings of counties that have similar geography, climate, and cropping practices (U.S. Department of Agriculture, National Agricultural Statistics Service, 2018a). Most states in our sample are each divided into nine adjacent CRDs. Clustering at this level is designed to mitigate the effects of spatial autocorrelation in the econometric errors.

"too close" (e.g., using other measures of spatial dependence, like Moran's I statistic) have not been fully explored.

5.3 Climate Change Beliefs, Attitudes, and Barriers to Adoption

Recent evidence suggests that the 2012 drought did not significantly affect agricultural advisors' climate change beliefs or adaptation attitudes. However, advisers indicated greater concern about risks from pests and drought arising from 2012 yield damages (Carlton et al., 2016). Against the current backdrop of learning requirements for progressing technologies and evolving drought risk (Lybbert and Bell, 2010), further research is needed to assess the potential of drought-tolerant crop varieties to serve as adaptation mechanisms. Although substantial field trial evidence confirms that DT corn has higher average yields relative to non-DT controls under water-stressed growing conditions (e.g. Gaffney et al., 2015; Nemali et al., 2015; Adee et al., 2016), this is not necessarily proof of its adaptation efficacy. Adoption of DT corn is an adaptation tool only if the economic gains from these varieties relative to conventional varieties under a changing climate are larger than the gains under a constant climate (Lobell, 2014).

Since the adoption data are only available for 2016, we cannot completely isolate short-run drought effects from circumstances surrounding the 2012 or adjacent-year droughts. This is of less concern if shocks similar in magnitude, timing, and duration to the 2012 drought are not exceptionally rare events, which seems unlikely under climate change. The ideal dataset, though, would contain repeated field-level observations over time, which would allow us to distinguish short-run effects from recent-year effects. However, to the extent that long-run drought risk will not lessen in coming years, our analysis suggests widespread disadoption of DT corn under current economic, technology, and policy environments is unlikely.

Moreover, we do not formally identify barriers to early DT corn adoption. In the context of sub-Saharan Africa, M. Fisher et al. (2015) find that poor market access, seed and labor availability, and lack of information about the new varieties hampered adoption of DT corn in 2012-13. Such factors are unlikely to significantly impact adoption in the U.S., where there are far fewer impediments to flows of seed, labor, capital, and information. Participation in Federal crop insurance is also unlikely to affect adoption in the U.S. (Weber, Key, and O'Donoghue, 2016; McFadden et al., 2019). However, seed premiums and farmers' perceptions of possible yield penalties could have decreased early adoption rates. We do not formally test this claim due to lack of price data. Rather, our results suggest U.S. DT corn adoption is mainly influenced by—and is likely to continue to be influenced by—drought exposure and risk.[24]

6 Conclusions and Policy Implications

Controlling for average weather conditions and the severity and duration of recent droughts, in addition to potentially-confounding location fixed effects, we find that adoption of DT corn is generally increasing in long-run average temperatures and drought risk. By contrast, adoption does not appear to be significantly affected by the severity of the worst drought experienced in the field in the previous five years, nor the duration of severe-or-worse droughts during this same period. Farmers are more likely to plant DT corn on highly erodible fields, and they are also less likely to irrigate on these fields, though the impact of irrigation on adoption is affected by soil type (i.e., clay-dominant particles).

There are three main caveats of this research. First, use of cross-sectional data has limited our ability to fully tease out the effects of field- and farm-specific factors on adoption. We have included a large set of covariates suggested by theory and past empirical evidence, though some relevant predictors may be absent from our regressions—–as is the case with nearly all cross-sectional analysis. Second, there are no widely-available data at fine spatially-varying scales for DT corn price premiums relative to prices of other corn varieties. Several empirical studies of climate change and agriculture assume an underlying market equilibrium such that prices are constant across space (Blanc and Reilly, 2017). Such an assumption is not unrealistic for integrated markets in the United States, but the existence of thousands

[24]The pace of DT corn adoption could increase if private seed companies increasingly combine drought tolerance with HT and/or Bt traits. Increased stacking could result from companies selling additional varieties with all three traits, or through a gradual market withdrawal of HT and/or Bt varieties that are not drought tolerant. The latter type of marketing strategy has been used for some types of farm machinery and technologies that—initially introduced as options—–gradually become standard equipment.

of agricultural cooperatives, seed retailers, and other agricultural input dealers suggests the likelihood of at least modest variability in seed prices across the country (e.g. Shi, Chavas, and Stiegert, 2010).[25] Third, the form of our analysis does not provide rigorous evidence about how uptake of drought-tolerant crop varieties could evolve under climate change. This type of analysis would make use of drought severity projections based on output from appropriately downscaled general circulation models (Hsiang and Kopp, 2018). Much progress has been made recently to forecast drought severity into the twenty-first century using climatological models (e.g. Cook, Ault, and Smerdon, 2015), but more research is necessary to generate a set of robust drought projections for use in climate economics studies.

A number of general policy implications emerge from our analysis. We find a negative relationship—though not generally statistically significant—between irrigation use and DT corn adoption, which is consistent with the notion that these technologies may not be complementary. Although irrigable fields are currently less likely to be planted to DT corn varieties, this relationship could fundamentally change as irrigation water sources become scarcer under a worsening climate. Faced with increasingly drier conditions, there could be some threshold beyond which irrigators would choose to adopt DT varieties if they perceive them to be a cost-effective way of limiting yield losses from mild-to-moderate droughts. However, if such a case were to occur, it is unknown if DT varieties would be chosen as a way to help preserve irrigation water availability (via the crop's improved water use efficiency) or if they would be chosen as a "last resort" option due to perceptions of yield penalties. In either case, decision-makers could consider availability and use of crops with greater water use efficiency when designing agricultural water policy.

In a similar vein, it is possible that U.S. farmers are using DT corn varieties as a kind of shallow loss insurance. That these varieties can serve as shallow loss insurance that complements conventional crop insurance policies is supported by the fact that: 1) drought tolerance does provide some yield loss protection against mild-to-moderate droughts, and 2) greater shares of DT corn fields than non-DT corn fields are insured under the U.S.

[25] Although evidence suggests that some spatial variability in drought-tolerant seed prices exist (e.g. Farmers Business Network, 2018), the extent to which this input price variability is tightly-linked to underlying agricultural productivity is unclear. By leaving out input prices, we minimize the risk of bias from bad control (Angrist and Pischke, 2008). However, we present results of a robustness check of our levels estimates to inclusion of state-level DT corn premiums in Appendix C of the Supplementary Information.

federal crop insurance program (McFadden et al., 2019). Regardless of mechanism, our results suggest adoption increases with average temperature and drought risk, which are both projected to increase under multiple climate scenarios. In the short run, optimal crop insurance premiums may need to be adjusted to account for the crop's greater resistance to drought, though these adjustments would likely need to be revisited as droughts intensify and become more prolonged.

Despite the positive linkages between temperature, drought risk, and adoption, farmers' learning about the net benefits of DT corn varieties could be hampered by random weather shocks during the growing season (Lybbert and Bell, 2010). For example, a farmer who chooses to plant DT corn, faces a substantially water-stressed growing season, and then suffers crop failure may believe that the DT variety or all similar varieties are ineffective even though they were not bred to thrive in such conditions. Conversely, a farmer who plants a DT corn variety could face routine weather conditions and a subsequently poor yield realization due to an unrelated factor (e.g., nutrient deficiency, pest infestation) but misattribute the outcome to a DT yield penalty. These scenarios suggest farmers' learning about DT seed efficacy is more challenging than that for other variable inputs (e.g., labor, fertilizer, energy, pesticides), reiterating the importance of extension programs. While these characteristics do not demonstrate a new role for extension, they highlight the need for clear communication of the idea that several years of data on DT seed use and experimentation may be required before farmers are able to make a fully-informed "final" determination of appropriateness of the technology for their operation.

A prime area for further research is a causal analysis of how weather shocks impact DT corn yields and net returns relative to their non-DT counterparts. The main private-sector companies selling DT corn varieties have published field trials demonstrating efficacy of the seeds under water-limited growing environments. Many but not all of these results have been replicated by university researchers on test plots, but there have been no studies that analyze the impacts of weather shocks on DT varieties' yields and economic returns using data on farmers' marketplace behavior across the United States. If implemented carefully, such a study would be able to inform policymakers and other market participants of the potential of drought tolerance, in isolation, to serve as a climate change adaptation mechanism.

References

Adee, E., K. Roozeboom, G.R. Balboa, A. Schlegel, and I.A. Ciampitti. 2016. Drought-Tolerant Corn Hybrids Yield More in Drought-Stressed Environments with No Penalty in Non-Stressed Environments. *Frontiers in Plant Science* 7: 1–9.

Angrist, J.D. and J.S. Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press.

Auffhammer, M. and W. Schlenker. 2014. Empirical Studies on Agricultural Impacts and Adaptation. *Energy Economics* 46: 551–561.

Barr, K.J., B.A. Babcock, M.A. Carriquiry, A.M. Nasser, and L. Harfuch. 2011. Agricultural Land Elasticities in the United States and Brazil. *Applied Economic Perspectives and Policy* 33 (3): 449–462.

Blanc, E. and J. Reilly. 2017. Approaches to Assessing Climate Change Impacts on Agriculture: An Overview of the Debate. *Review of Environmental Economics and Policy* 11 (2): 247–257.

Burke, M. and K. Emerick. 2016. Adaptation to Climate Change: Evidence from U.S. Agriculture. *American Economic Journal: Economic Policy* 8 (3): 106–140.

Carlton, J.S., A.S. Mase, C.L. Knutson, M.C. Lemos, T. Haigh, D.P. Todey, and L.S. Prokopy. 2016. Adaptation to Climate Change: Evidence from U.S. Agriculture. *Climatic Change* 135 (2): 211–226.

Castiglioni, P., D. Warner, R.J. Bensen, D.C. Anstrom, J. Harrison, M. Stoecker, M. Abad, G. Kumar, S. Salvador, R. D'Ordines, S. Navarro, S. Back, M. Fernandes, J. Targolli, S. Dasgupta, C. Bonin, M.H. Luethy, and J.E. Heard. 2008. Bacterial RNA Chaperones Confer Abiotic Stress Tolerance in Plants and Improved Grain Yield in Maize under Water-Limited Conditions. *Plant Physiology* 147 (2): 446–455.

Chambers, R.G. and J. Quiggin. 2000. *Uncertainty, Production, Choice, and Agency: The State-Contingent Approach*. Cambridge, UK: Cambridge University Press.

Cook, B.I., T.R. Ault, and J.E. Smerdon. 2015. Unprecedented 21st Century Drought Risk in the American Southwest and Central Plains. *Science Advances* 1 (1): 1–7.

Cooper, M., C. Gho, R. Leafren, T. Tang, and C. Messina. 2014. Breeding Drought-Tolerant Maize Hybrids for the U.S. Corn Belt: Discovery to Product. *Journal of Experimental Botany* 65 (21): 6191–6204.

Daly, C., R.P. Neilson, and D.L. Phillips. 1994. A Statistical-Topographic Model for Mapping Climatological Precipitation Over Mountainous Terrain. *Journal of Applied Meteorology* 33 (2): 140–158.

Deschênes, O. and M. Greenstone. 2007. The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather. *American Economic Review* 97 (1): 354–385.

Dobos, R., H. Sinclair Jr., and M. Robotham. 2012. *User Guide for the National Commodity Crop Productivity Index*. Website. Accessed on 04/29/2018. U.S. Department of Agriculture. URL: https://www.nrcs.usda.gov/wps/portal/nrcs/site/national/home.

Druckenmiller, H. and S. Hsiang. 2018. *Accounting for Unobservable Heterogeneity in Cross Section Using Spatial First Differences*. Working Paper 25177. National Bureau of Economic Research (NBER).

Edmeades, G.O. 2012. Progress in Achieving and Delivering Drought Tolerance in Maize – An Update. *Global Status of Commercialized Biotech/GM Crops: 2012, Brief 44*. Ed. by C. James. Ithaca, NY: The International Service for the Acquisition of Agri-biotech Applications (ISAAA): 239–272.

Farmers Business Network. 2018. *Zone Pricing in Corn Seed Report*. Website. Accessed on 04/09/18. URL: https://emergence.fbn.com.

Fernandez-Cornejo, J. and W.D. McBride. 2002. *Adoption of Bioengineered Crops*. AER-810. U.S. Department of Agriculture, Economic Research Service.

Fisher, M., T. Abate, R.W. Lunduka, M. Asnake, Y. Alemayehu, and R.B. Madulu. 2015. Drought Tolerant Maize for Farmer Adaptation to Drought in Sub-Saharan Africa: Determinants of Adoption in Eastern and Southern Africa. *Climatic Change* 133 (2): 283–299.

Gaffney, J., J. Schussler, C. Löffler, W. Cai, S. Paszkiewicz, C. Messina, J. Groeteke, J. Keaschall, and M. Cooper. 2015. Industry-Scale Evaluation of Maize Hybrids Selected for Increased Yields in Drought-Stress Conditions of the U.S. Corn Belt. *Crop Science* 55 (4): 1608–1618.

Heddinghaus, T.R. and P. Sabol. 1991. Review of the Palmer Drought Severity Index and Where Do We Go from Here? *Proceedings, 7th Conference on Applied Climatology.* Boston, MA: American Meterological Society: 242–246.

Heisey, P.W. and K. Day Rubenstein. 2015. *Using Crop Genetic Resources to Help Agriculture Adapt to Climate Change: Economics and Policy.* EIB-139. U.S. Department of Agriculture, Economic Research Service.

Hsiang, S. 2016. Climate Econometrics. *Annual Review of Resource Economics* 8: 43–75.

Hsiang, S. and R.E. Kopp. 2018. *An Economist's Guide to Climate Change Science.* Working Paper 25189. National Bureau of Economic Research (NBER).

Intergovernmental Panel on Climate Change. 2014. Climate Change 2014: Synthesis Report. *Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Geneva, Switzerland: ICPP.

International Maize and Wheat Improvement Center (CIMMYT). 2018. *Project Profiles.* Website. Accessed on 05/02/18. CIMMYT. URL: https://www.cimmyt.org/project-profile.

Kahneman, D. and A. Tversky. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47 (2): 263–292.

Kuwayama, Y., A. Thomspon, R. Bernknopf, and B. Zaitchik. 2019. Estimating the Impact of Drought on Agriculture Using the U.S. Drought Monitor. *American Journal of Agricultural Economics* 101 (1): 193–210.

Lin, W., G.W. Dean, and C.V. Moore. 1974. An Empirical Test of Utility vs. Profit Maximization in Agricultural Production. *American Journal of Agricultural Economics* 56 (3): 497–508.

Lobell, D.B. 2014. Climate Change Adaptation in Crop Production: Beware of Illusions. *Global Food Security* 3 (2): 72–76.

Lybbert, T.J. and A. Bell. 2010. Stochastic Benefit Streams, Learning, and Technology Diffusion: Why Drought Tolerance is Not the New Bt. *AgBioForum* 13 (1): 13–24.

McFadden, J.R., D.J. Smith, S.J. Wechsler, and S. Wallander. 2019. *Development, Adoption, and Management of Drought-Tolerant Corn in the United States*. EIB-204. U.S. Department of Agriculture, Economic Research Service.

Mendelsohn, R., W.D. Nordhaus, and D. Shaw. 1994. The Impact of Global Warming on Agriculture: A Ricardian Analysis. *American Economic Review* 84 (4): 753–771.

Minford, M. 2015. *Farmers Test Drought-Tolerant Corn Hybrids*. Website. Accessed on 04/12/18. Corn and Soybeans Digest. URL: http://www.cornandsoybeandigest.com/corn.

Nemali, K.S., C. Bonin, F.G. Dohleman, M. Stephens, W.R. Reeves, D.E. Nelson, P. Castiglioni, J.E. Whitsel, B. Sammons, R.A. Silady, D. Anstrom, R.E. Sharp, O.R. Patharkar, D. Clay, M. Coffin, M.A. Nemeth, M.E. Leibman, M. Luethy, and M. Lawson. 2015. Physiological Responses Related to Increased Grain Yield under Drought in the First Biotechnology-Derived Drought-Tolerant Maize. *Plant, Cell, and Environment* 38 (9): 1866–1880.

Nuccio, M.L., M. Paul, N.J. Bate, J. Cohn, and S.R. Cutler. 2018. Where are the Drought Tolerant crops? An Assessment of More than Two Decades of Plant Biotechnology Effort in Crop Improvement. *Plant Science* 273: 110–119.

Powlson, D.S., C.M. Stirling, M.L. Jat, B.G. Gerard, C.A. Palm, P.A. Sanchez, and K.G. Cassman. 2014. Limited Potential of No-Till Agriculture for Climate Change Mitigation. *Nature Climate Change* 4: 678–683.

Rippey, B.R. 2015. The U.S. Drought of 2012. *Weather and Climate Extremes* 10 (A): 57–64.

Schlenker, W., W.M. Hanemann, and A.C. Fisher. 2005. Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach. *American Economic Review* 95 (1): 395–406.

Schlenker, W. and M.J. Roberts. 2009. Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields under Climate Change. *Proceedings of the National Academy of Sciences* 106 (37): 15594–15598.

Schoemaker, P.J.H. 1982. The Expected Utility Model: Its Variants, Purposes, Evidence, and Limitations. *Journal of Economic Literature* 20 (2): 529–563.

Shi, G., J.P. Chavas, and K. Stiegert. 2010. An Analysis of the Pricing of Traits in the U.S. Corn Seed Market. *American Journal of Agricultural Economics* 92 (5): 1324–1338.

Steward, D.R., P.J. Bruss, X. Yang, S.A. Staggenborg, S.M. Welch, and M.D. Apley. 2013. Tapping Unsustainable Groundwater Stores for Agricultural Production in the High Plains Aquifer of Kansas, Projections to 2110. *Proceedings of the National Academy of Sciences* 110 (37): E3477–E3486.

Strzepek, K., G. Yohe, J. Neumann, and B. Boehlert. 2010. Characterizing Changes in Drought Risk for the United States from Climate Change. *Environmental Research Letters* 5 (4): 1–9.

U.S. Department of Agriculture, Economic Research Service. 2016. *Agricultural Resource Management Survey: Overview*. Website. Accessed on 06/05/19. URL: https://www.ers.usda.gov/data-products.

— 2022. *U.S. Farm Income and Wealth Statistics*. Website. Accessed on 03/30/22. URL: https://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/.

U.S. Department of Agriculture, National Agricultural Statistics Service. 2013. *Census of Agriculture, 2012*. Website. Accessed on 06/23/22. URL: https://www.nass.usda.gov/AgCensus/index.php.

— 2018a. *County Data FAQs*. Website. Accessed on 07/01/19. URL: https://www.nass.usda.gov/Data_and_Statistics/index.php.

— 2018b. *Quick Stats*. Website. Accessed on 02/11/19. URL: https://quickstats.nass.usda.gov.

— 2022. *Acreage*. Website. Accessed on 03/30/22. URL: https://www.nass.usda.gov/Publications/Todays_Reports/reports/acrg0621.pdf.

U.S. Department of Agriculture, Natural Resources Conservation Service. 2018. *Gridded Soil Survey Geographic Database for the Coterminous United States*. Website. Accessed on 10/16/18. URL: https://gdg.sc.egov.usda.gov/.

U.S. Drought Monitor. 2019. *Drought Classification*. Website. Accessed on 03/28/19. URL: http://droughtmonitor.unl.edu/Data.aspx.

Wallander, S., M. Aillery, D. Hellerstein, and M. Hand. 2013. *The Role of Conservation Programs in Drought Risk Adaptation*. ERR-144. U.S. Department of Agriculture, Economic Research Service.

Waltz, E. 2014. Beating the Heat. *Nature Biotechnology* 32 (7): 610–613.

Weber, J.G., N. Key, and E. O'Donoghue. 2016. Does Federal Crop Insurance Make Environmental Externalities from Agriculture Worse? *Journal of the Association of Environmental and Resource Economists* 3 (3): 707–742.

Wooldridge, J.M. 2010. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wossen, T., T. Abdoulaye, A. Alene, S. Feleke, A. Menkir, and V. Manyong. 2017. Measuring the Impacts of Adaptation Strategies to Drought Stress: The Case of Drought Tolerant Maize Varieties. *Journal of Environmental Management* 203 (1): 106–113.

Wozniak, G.D. 1987. Human Capital, Information, and the Early Adoption of New Technology. *Journal of Human Resources* 22 (1): 101–112.

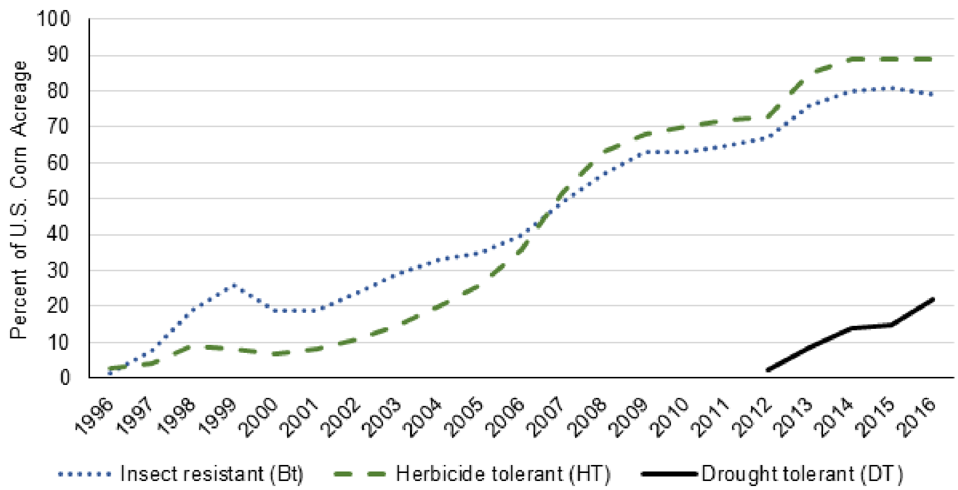

Figure 1: Adoption of insect-resistant, herbicide-tolerant, and drought-tolerant corn in the United States since 1996.
Note: The HT and Bt genetically-engineered (GE) traits were commercially introduced in corn in 1996. The year in which GE varieties of drought-tolerant (DT) corn were introduced was 2012. For year 2016, the DT adoption rate is calculated from Phase II ARMS data. Since Phase II of ARMS does not survey corn each year, estimates of adoption rates are unavailable prior to 2016. For years 2012-15, DT corn acreage is taken from various industry sources and then divided by total harvested acreage of corn for grain. Adoption rates for Bt and HT corn include minimal acreages of stacked varieties (1996-2000), whereas adoption rates for DT corn include varieties that are overwhelmingly stacked with Bt and/or HT traits (2012-2016).
Source: Fernandez-Cornejo and McBride (2002) for Bt and HT corn adoption rates; USDA, National Agricultural Statistics Service (2018) and various industry estimates for DT (2011-15); USDA, Economic Research Service and National Agricultural Statistics Service, 2016 Agricultural Resource Management Survey.

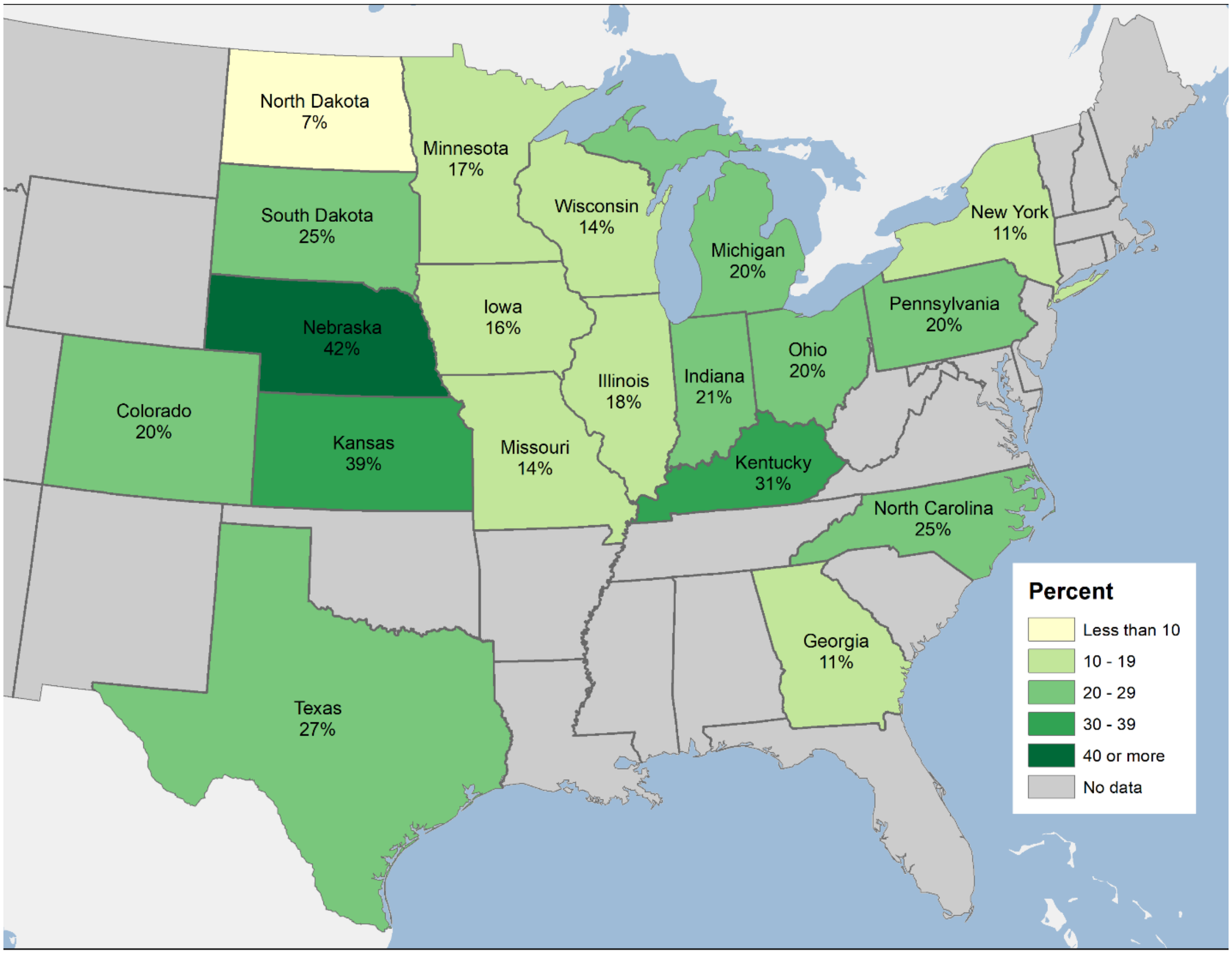

Figure 2: DT shares of U.S. state corn acreage, 2016.
Note: In 2016, total U.S. corn acreage planted to DT varieties was 18.6 million acres.
Source: USDA, Economic Research Service and National Agricultural Statistics Service, 2016 Agricultural Resource Management Survey.

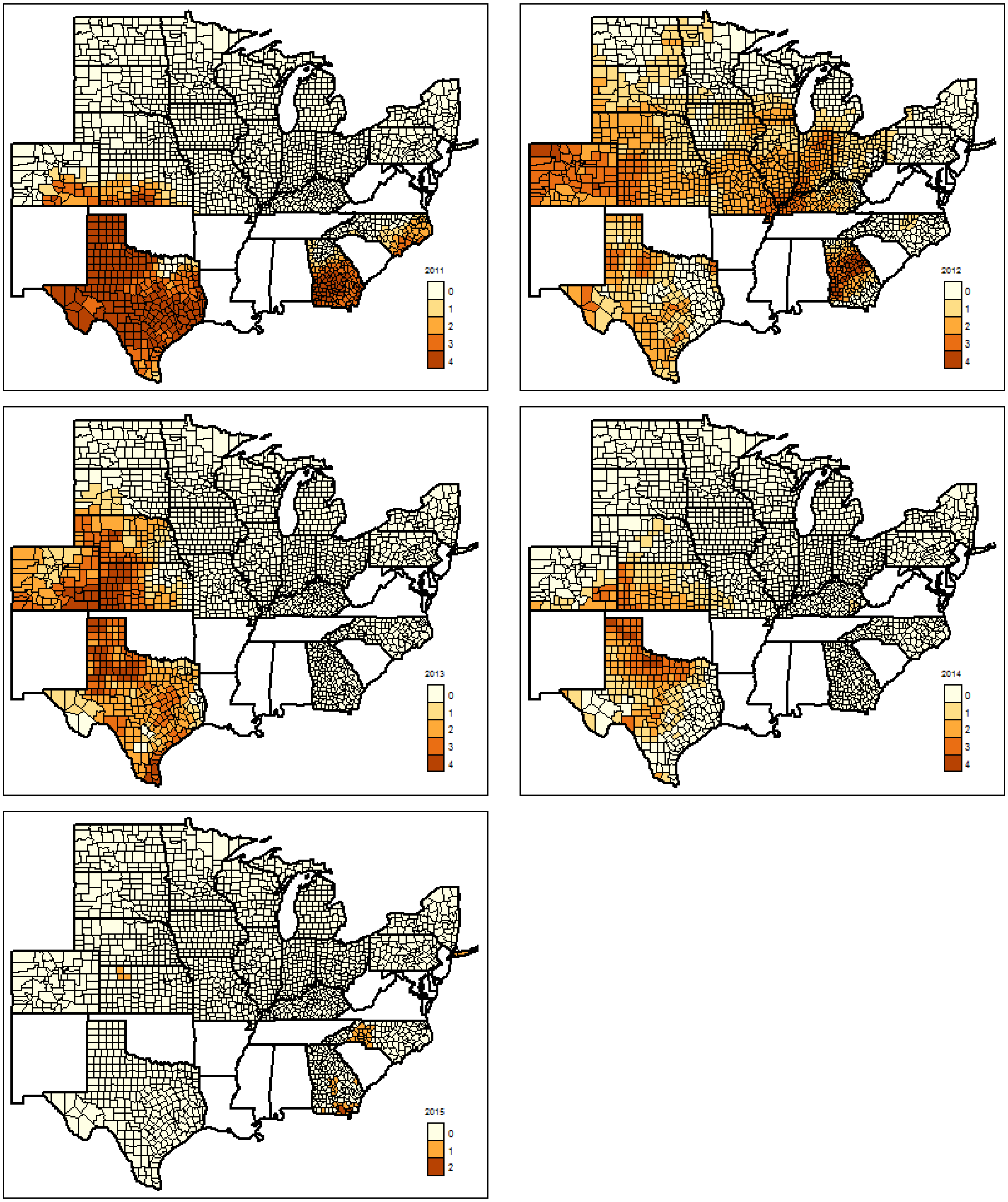

Figure 3: U.S. Drought Monitor index of droughts, 2011-15.
Note: The U.S. Drought Monitor sorts drought into five categories: abnormally dry (a drought precursor, D0), moderate (D1), severe (D2), extreme (D3), and exceptional (D4). These can be thought of in terms of potential impacts: short-term dryness (D0), some damage to crops (D1), crop losses likely (D2), major crop losses (D3), and exceptional and widespread crop losses (D4), although actual agricultural impacts will vary by crop and irrigation use.
Source: U.S. Drought Monitor, 2019.

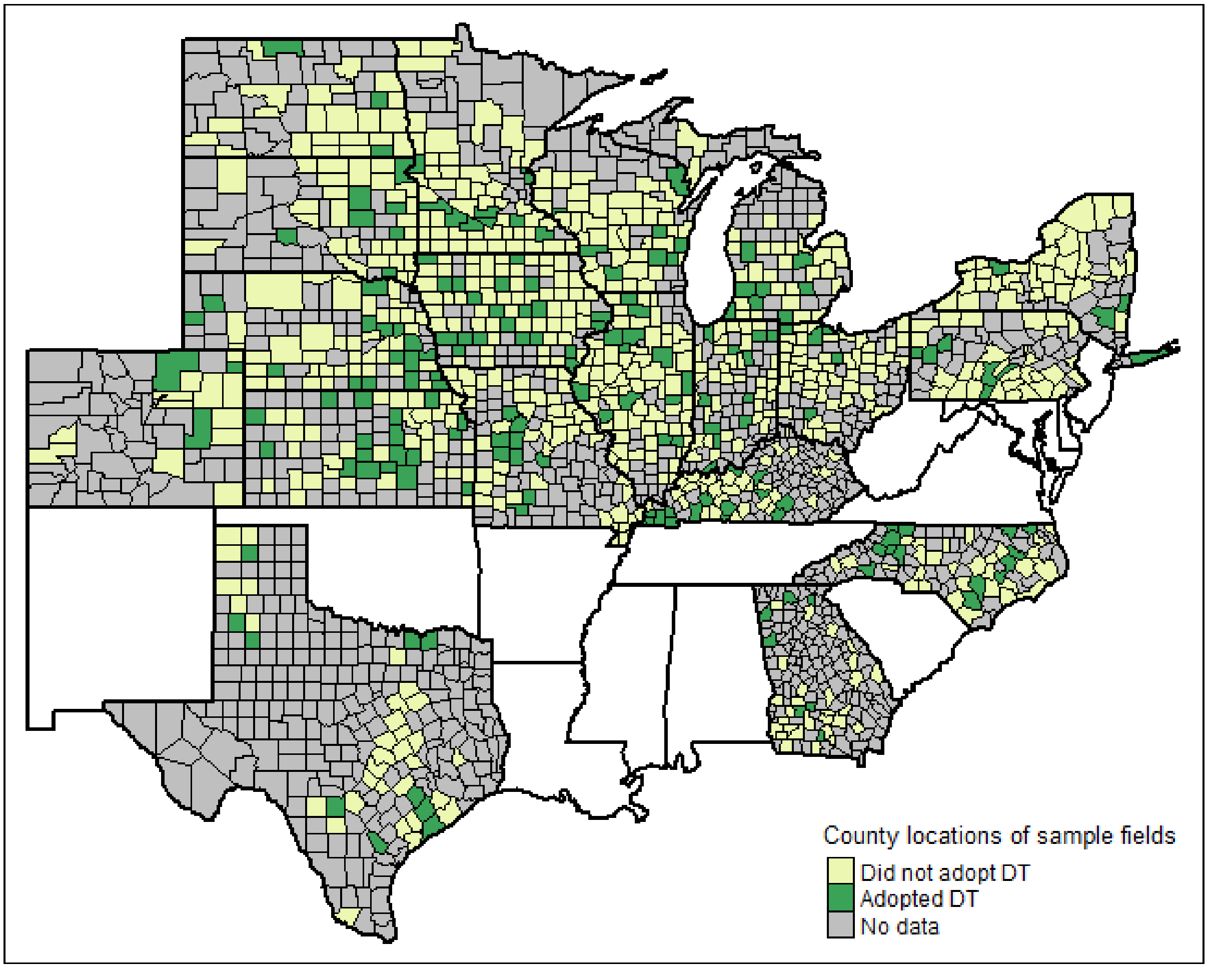

Figure 4: U.S. county adoption of DT corn, 2016.
Note: All surveyed states in 2016 are depicted (Colorado, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, New York, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, Texas, and Wisconsin). Multiple fields per county appear in the dataset frequently, and within these counties, there can be several fields planted with DT varieties. The maximum number of DT fields per county was six.
Source: USDA, Economic Research Service and National Agricultural Statistics Service, 2016 Agricultural Resource Management Survey.

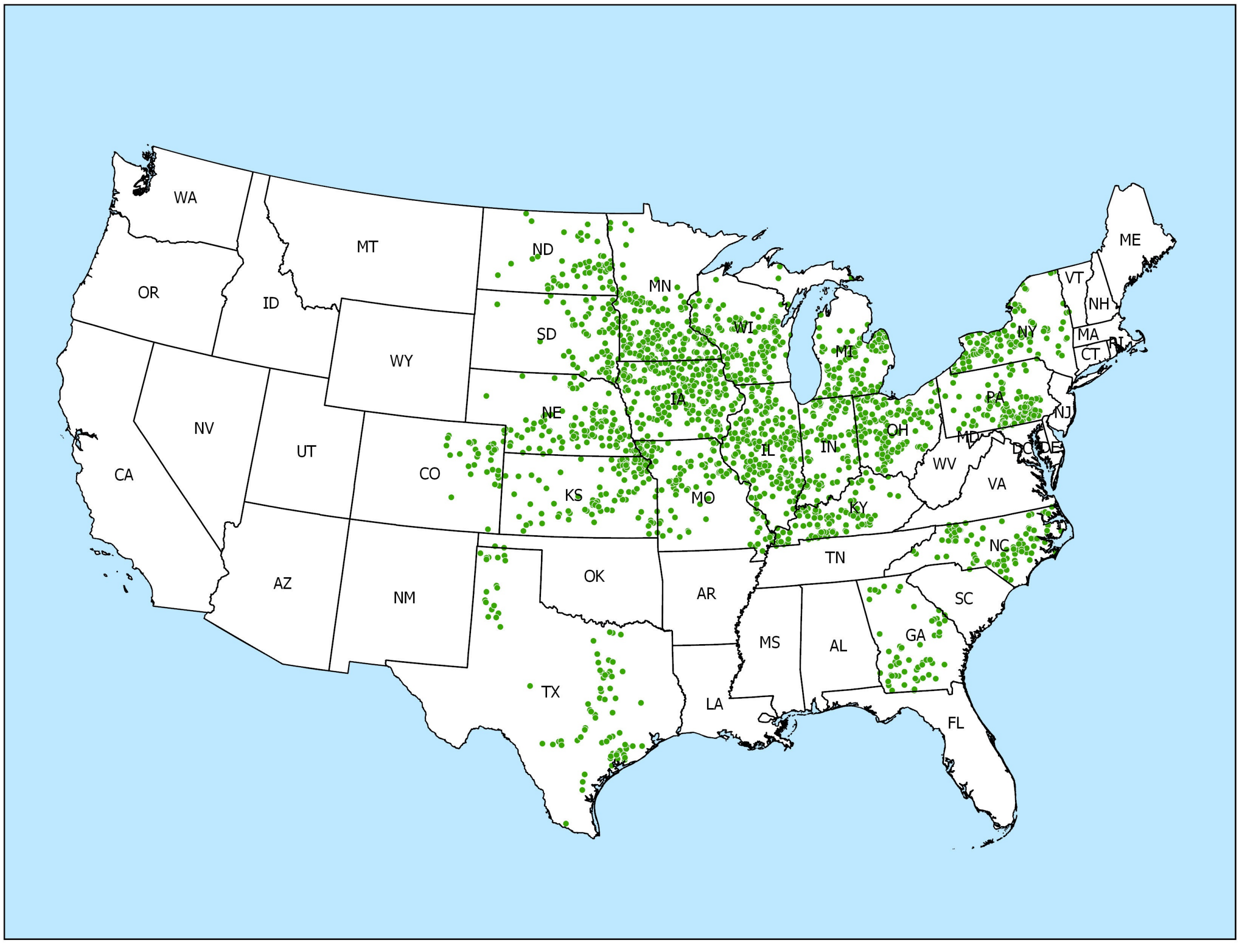

Figure 5: Surveyed fields' locations, 2016.
Note: To preserve privacy and meet USDA data disclosure requirements, dots representing field locations are disproportionately large relative to map scale.
Source: USDA, Economic Research Service and National Agricultural Statistics Service, 2016 Agricultural Resource Management Survey.

Table 1: Summary Statistics (n = 1,768 fields)

	Units	Sample Mean	Weighted Mean	Standard Error	Min	Max
2016 DT adoption rate	{0,1}	0.21	0.20	0.02	0	1
Severe-or-greater drought duration	Months	4.78	4.45	0.44	0	45
Maximum drought intensity	Index	3.67	3.57	0.11	−0.56	7.57
Drought risk	$[0,\infty)$	2.27	2.26	0.03	1.60	3.08
30-year temp. mean	°C	20.82	20.50	0.19	16.57	28.03
30-year temp. std. dev.	°C	1.42	1.43	0.01	0.84	1.80
30-year precip. mean	In.	4.02	4.11	0.04	1.91	5.69
30-year precip. std. dev.	In.	1.96	2.03	0.03	0.95	2.92
Irrigation	{0,1}	0.10	0.06	0.02	0	1
Irrigation x non-irr. corn share	[0,1]	0.03	0.02	0.005	0	0.99
Clay	{0,1}	0.13	0.15	0.02	0	1
Irrigation x clay	{0,1}	0.01	0.004	0.002	0	1
Irrigation x non-irr. corn share x clay	[0,1]	0.002	0.001	0.001	0	0.94
Highly erodible	{0,1}	0.14	0.17	0.02	0	1
Corn-soy soil index – mean	[0,10]	5.72	6.01	0.16	0.35	9.59
Corn-soy soil index – std. dev.	$[0, \infty)$	1.09	1.18	0.04	0	3.38
February 2016 basis	$ (USD)	−0.12	−0.15	0.03	−0.80	1.13

Note: Estimates are expanded to the population of U.S. corn fields in 2016 using a base expansion factor from NASS. Standard errors are clustered at the crop reporting district (CRD) level. There are 142 CRDs in the full sample with 12.5 fields per CRD, on average.

Table 2: Mean-Variance-based Model: Weighted Linear Probability Model Estimates and Probit Average Marginal Effects

	LPM (marginal effects)			Probit (average marginal effects)		
	(1a) Drought risk & climate	(2a) Drought risk only	(3a) Climate only	(1b) Drought risk & climate	(2b) Drought risk only	(3b) Climate only
Drought risk	0.106	0.197**		0.103	0.198**	
	(0.076)	(0.078)		(0.077)	(0.079)	
30-year temp. mean	0.024**		0.026**	0.024**		0.026**
	(0.011)		(0.011)	(0.010)		(0.010)
30-year temp. std. dev.	0.097		0.165	0.134		0.193
	(0.214)		(0.205)	(0.208)		(0.201)
30-year precip. mean	−0.075		−0.097	−0.072		−0.095
	(0.059)		(0.062)	(0.061)		(0.060)
30-year precip. std. dev.	0.103		0.138*	0.096		0.134*
	(0.082)		(0.081)	(0.083)		(0.081)
Irrigation	−0.117	−0.076	−0.091	−0.092*	−0.068	−0.076
	(0.075)	(0.069)	(0.071)	(0.055)	(0.058)	(0.057)
Irrigation x non-irrigated corn share	0.105	0.073	0.073	0.092	0.067	0.067
	(0.126)	(0.122)	(0.122)	(0.132)	(0.127)	(0.130)
Clay	0.011	0.011	0.008	0.011	0.010	0.008
	(0.037)	(0.036)	(0.037)	(0.037)	(0.036)	(0.037)
Irrigation x clay	0.659**	0.629**	0.675**	0.639***	0.613***	0.653***
	(0.269)	(0.270)	(0.268)	(0.205)	(0.225)	(0.191)
Irrigation x non-irrigated corn share x clay	−0.747	−0.674	−0.749	−0.569	−0.505	−0.579
	(0.591)	(0.588)	(0.592)	(0.478)	(0.481)	(0.480)
Highly erodible	0.073*	0.078**	0.075*	0.072*	0.077**	0.073*
	(0.038)	(0.038)	(0.038)	(0.037)	(0.038)	(0.038)
Corn-soy soil index mean	−0.006	−0.001	−0.006	−0.005	−0.001	−0.006
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Corn-soy soil index std. dev.	0.016	0.019	0.006	0.017	0.019	0.008
	(0.027)	(0.027)	(0.025)	(0.027)	(0.027)	(0.025)
February 2016 basis	0.073	0.109**	0.049	0.086	0.112**	0.061
	(0.082)	(0.049)	(0.082)	(0.082)	(0.050)	(0.081)
Constant	−0.541	−0.257	−0.423			
	(0.384)	(0.187)	(0.369)			
Observations	1,768	1,768	1,768	1,768	1,768	1,768
Correctly classified (%)	79	79	79	79	79	79
F-statistic	2.37***	2.75***	2.33***	2.37***	2.61***	2.36***
R-squared	0.03	0.02	0.03			

Note: Estimates are expanded to the population of U.S. corn fields in 2016 using a base expansion factor from NASS. Standard errors in parentheses are clustered at the crop reporting district (CRD) level. For the LPM estimates, all predicted probabilities were within the unit interval. Goodness-of-fit statistics for the probit regressions are with respect to the fitted model. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.

Table 3: Prospect-Theory-based Model: Weighted Linear Probability Model Estimates and Probit Average Marginal Effects

	LPM (marginal effects)		Probit (average marginal effects)	
	(1a) Drought shocks & climate	(2a) Drought shocks only	(1b) Drought shocks & climate	(2b) Drought shocks only
Severe-or-greater drought duration	0.002	0.002	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Maximum drought intensity	−0.006	0.022	−0.006	0.022
	(0.018)	(0.017)	(0.017)	(0.017)
30-year temp. mean	0.027**		0.027**	
	(0.011)		(0.011)	
30-year temp. std. dev.	0.183		0.208	
	(0.220)		(0.213)	
30-year precip. mean	−0.096		−0.094	
	(0.060)		(0.060)	
30-year precip. std. dev.	0.136		0.131	
	(0.085)		(0.083)	
Irrigation	−0.093	−0.079	−0.080	−0.073
	(0.083)	(0.074)	(0.064)	(0.061)
Irrigation x non-irrigated corn share	0.077	0.059	0.074	0.063
	(0.125)	(0.122)	(0.134)	(0.132)
Clay	0.007	0.010	0.007	0.009
	(0.038)	(0.037)	(0.038)	(0.036)
Irrigation x clay	0.679**	0.649**	0.656***	0.633***
	(0.270)	(0.272)	(0.189)	(0.207)
Irrigation x non-irrigated corn share x clay	−0.757	−0.664	−0.586	−0.511
	(0.597)	(0.585)	(0.479)	(0.484)
Highly erodible	0.073*	0.080**	0.072*	0.080**
	(0.038)	(0.039)	(0.037)	(0.039)
Corn-soy soil index mean	−0.007	−0.001	−0.006	−0.001
	(0.008)	(0.008)	(0.008)	(0.008)
Corn-soy soil index std. dev.	0.006	0.007	0.009	0.008
	(0.026)	(0.027)	(0.026)	(0.027)
February 2016 basis	0.057	0.036	0.070	0.037
	(0.084)	(0.045)	(0.083)	(0.045)
Constant	−0.456	0.107		
	(0.401)	(0.067)		
Observations	1,768	1,768	1,768	1,768
Correctly classified (%)	79	79	79	79
F-statistic	2.04**	1.60	2.06**	1.50
R-squared	0.03	0.02		

Note: Estimates are expanded to the population of U.S. corn fields in 2016 using a base expansion factor from NASS. Standard errors (not shown) are clustered at the crop reporting district (CRD) level. Goodness-of-fit statistics for the probit regressions are with respect to the fitted model. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.

Table 4: Summary Statistics, Spatial First Differenced Data

	Mi. < 14		Mi. < 9		Mi. < 6	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2016 drought-tolerant corn adoption	0.014	0.516	0.027	0.532	0.045	0.534
Severe-or-greater drought duration	−0.042	2.037	−0.013	1.846	0.011	1.465
Maximum drought intensity	0.013	0.403	0.002	0.363	−0.005	0.278
Drought risk	0.001	0.066	0.002	0.053	−0.002	0.039
30-year temp. mean	−0.003	0.360	−0.003	0.284	0.008	0.208
30-year temp. std. dev.	0.001	0.022	0.001	0.020	0.001	0.020
30-year precip. mean	−0.004	0.114	−0.004	0.102	0.003	0.097
30-year precip. std. dev.	−0.004	0.091	−0.003	0.082	0.001	0.075
Irrigation	0.006	0.246	0.007	0.249	0.008	0.231
Irrigation x non-irrigated corn share	0.008	0.160	0.008	0.157	0.011	0.155
Clay	−0.005	0.449	−0.031	0.435	−0.056	0.439
Irrigation x clay	−0.002	0.080	−0.007	0.080	−0.011	0.105
Irrigation x non-irrigated corn share x clay	0.0001	0.040	−0.002	0.029	−0.003	0.038
Highly erodible	0.002	0.445	0.010	0.453	0.011	0.443
Corn-soy soil index mean	−0.007	0.080	−0.010	0.073	−0.009	0.065
Corn-soy soil index std. dev.	0.001	0.042	−0.0003	0.041	0.0003	0.038
February 2016 basis	0.002	0.039	−0.001	0.029	0.0002	0.023

Note: For all regressors except the two soil index variables and February 2016 basis, the sample sizes are the following: 929 fields (mi. < 14), 615 fields (mi. < 9), and 358 fields (mi. < 6).

Table 5: Spatial First Difference Estimates at the 75th, 50th, and 25th Percentiles of Distance between Fields

	SFD			Levels		
	Mi. < 14 (1a)	Mi. < 9 (2a)	Mi. < 6 (3a)	Mi. < 14 (1b)	Mi. < 9 (2b)	Mi. < 6 (3b)
Severe-or-greater drought duration	−0.008	−0.022	−0.042	−0.0003	−0.002	−0.003
	(0.018)	(0.028)	(0.049)	(0.005)	(0.005)	(0.005)
Maximum drought intensity	−0.025	−0.095*	−0.072	0.009	−0.002	0.026
	(0.057)	(0.057)	(0.121)	(0.028)	(0.027)	(0.032)
30-year temp. mean				0.039**	0.044**	0.050**
				(0.017)	(0.018)	(0.021)
30-year temp. std. dev.				0.338	0.460	0.680*
				(0.321)	(0.380)	(0.372)
30-year precip. mean				0.045	0.031	0.052
				(0.078)	(0.092)	(0.100)
30-year precip. std. dev.				−0.028	−0.007	0.038
				(0.107)	(0.122)	(0.148)
Irrigation	−0.293**	−0.318	−0.150	−0.067	−0.192**	−0.116
	(0.148)	(0.232)	(0.286)	(0.139)	(0.083)	(0.112)
Irrigation x non-irrigated corn share	0.315	0.279	0.091	−0.009	0.052	−0.103
	(0.244)	(0.305)	(0.373)	(0.186)	(0.145)	(0.130)
Clay	−0.095	−0.111	−0.263**	−0.040	−0.020	−0.023
	(0.057)	(0.078)	(0.126)	(0.029)	(0.041)	(0.048)
Irrigation x clay	0.714*	0.964***	1.083**	0.375	0.912***	
	(0.366)	(0.318)	(0.483)	(0.481)	(0.130)	
Irrigation x non-irrigated corn share x clay	−0.883	−1.661**	−1.582	0.358		
	(0.610)	(0.669)	(0.988)	(0.560)		
Highly erodible	0.058	0.111	0.071	0.059	0.119**	0.046
	(0.063)	(0.074)	(0.071)	(0.045)	(0.054)	(0.064)
Corn-soy soil index mean	0.768**	0.406	0.219	−0.036	−0.057	−0.035
	(0.307)	(0.326)	(0.604)	(0.117)	(0.147)	(0.165)
Corn-soy soil index std. dev.	0.509	0.016	0.485	−0.267	−0.421	−0.899***
	(0.457)	(0.427)	(0.675)	(0.283)	(0.305)	(0.335)
February 2016 basis				0.061	0.083	0.106
				(0.123)	(0.139)	(0.155)
Constant	−0.027	−0.031	−0.032	−1.120*	−1.400*	−1.845**
	(0.023)	(0.027)	(0.050)	(0.651)	(0.720)	(0.702)
Observations	925	613	356	926	614	357
Correctly classified (%)	79	81	83	80	80	83
R-squared	0.03	0.04	0.08	0.03	0.06	0.07
Clusters	113	99	91	113	99	91

Note: Estimates are expanded to the population of U.S. corn fields in 2016 using a base expansion factor from NASS. Standard errors (not shown) are clustered at the crop reporting district (CRD) level. Linear probability models in (1b), (2b), and (3b) are estimated for the regressions in level terms. The R-squared values for the SFD estimates are analogous to the within R-squared from a fixed effects panel estimator, while the R-squared for the levels models (LPMs) are overall R-squared values. Irrigation-related interaction terms are dropped in the specifications of the last two columns due to multicollinearity. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.