Weather, Climate, 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 drought risk and recent drought exposure has led to this adoption. 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 new econometric method, spatial first differences, that can reduce concerns of omitted variables bias. Controlling for drought severity, frequency, and recentness, we find that drought exposure during 2011-14 and longer-run drought risk led to increased adoption of DT varieties in 2016. We predict that current national uptake of DT varieties would have been 10 percentage points lower had widespread drought not occurred in 2013.

JEL Codes: Q12, Q15, Q16, Q54

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

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[*]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, some applied econometric studies have found little evidence of long-run adaptation to climate change in the production of major U.S. row crops. 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.

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 exposure to droughts between 2011 and 2014 led to increased adoption of DT varieties, with adoption generally increasing in drought severity and exposure to long-run drought risk. Using our preferred model estimates, we predict that current national uptake of drought-tolerant varieties would have been 10 percentage points lower, on average, had widespread drought not occurred during 2013.

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. Under this approach, field trial data were assessed to identify a set of high-potential hybrids. The genetic composition of these hybrids were then analyzed, with subsequent statistical predictions about their yield performance and other traits under drought conditions. A subset of these were then released after further field tests across multiple site-year combinations (Gaffney et al., 2015).[2] Non-GE DT corn acreage has increased following its 2011 commercial release (Minford, 2015).

GE drought tolerance involves insertion of a gene from the soil bacterium Bacillus subtilis

[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), intends to develop 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]Non-GE DT varieties exhibit differences in water use efficiency relative to non-DT varieties. Reduced transpiration during high vapor pressure deficit (Messina et al., 2015) could result in a greater fraction of the plant's water diverted to kernel growth rather than survival during flowering (Cooper et al., 2014; Gaffney et al., 2015).

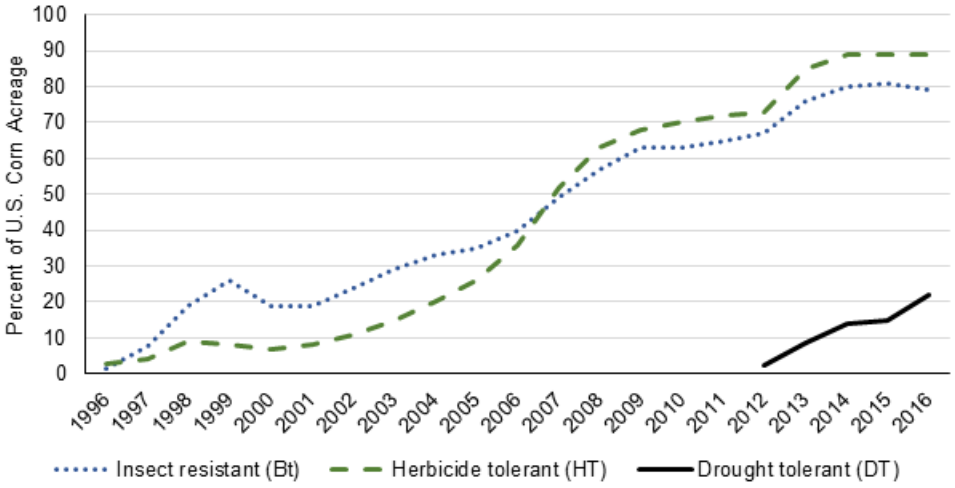


Figure 1: Adoption of insect-resistant, herbicide-tolerant, and drought-tolerant corn in the United States since 1996. Notes: The HT and Bt genetically-engineered (GE) traits were commercially introduced in corn in 1996. The year in which GE varieties of drought-tolerant (DT) corn were introduced was 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 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.

into the genetic material of the corn plant. This gene causes expression of cold shock protein B (cspB), which binds to certain molecules and "unfolds" some molecular structures that "fold" during drought. This mitigates the effects of drought on photosynthesis, carbon dioxide movement through leaves, and conversion of inorganic carbon.[3] Similar to non-GE varieties, 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).

The percent of U.S. corn acreage planted to DT corn varieties has increased swiftly in the years following commercialization (fig. 1). In 2012, DT corn (both GE and non-GE varieties) accounted for a little over 2% of national corn acreage. By 2016, roughly 22%

[3]Ongoing research seeks to identify how cspB expression contributes to improved yield performance under drought. For example, some research finds that reduced leaf growth during the silking stage can increase water use efficiency, which can result in larger ears with greater kernel development (Nemali et al., 2015).

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) GE 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 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.

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.

As expected, adoption is highly 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

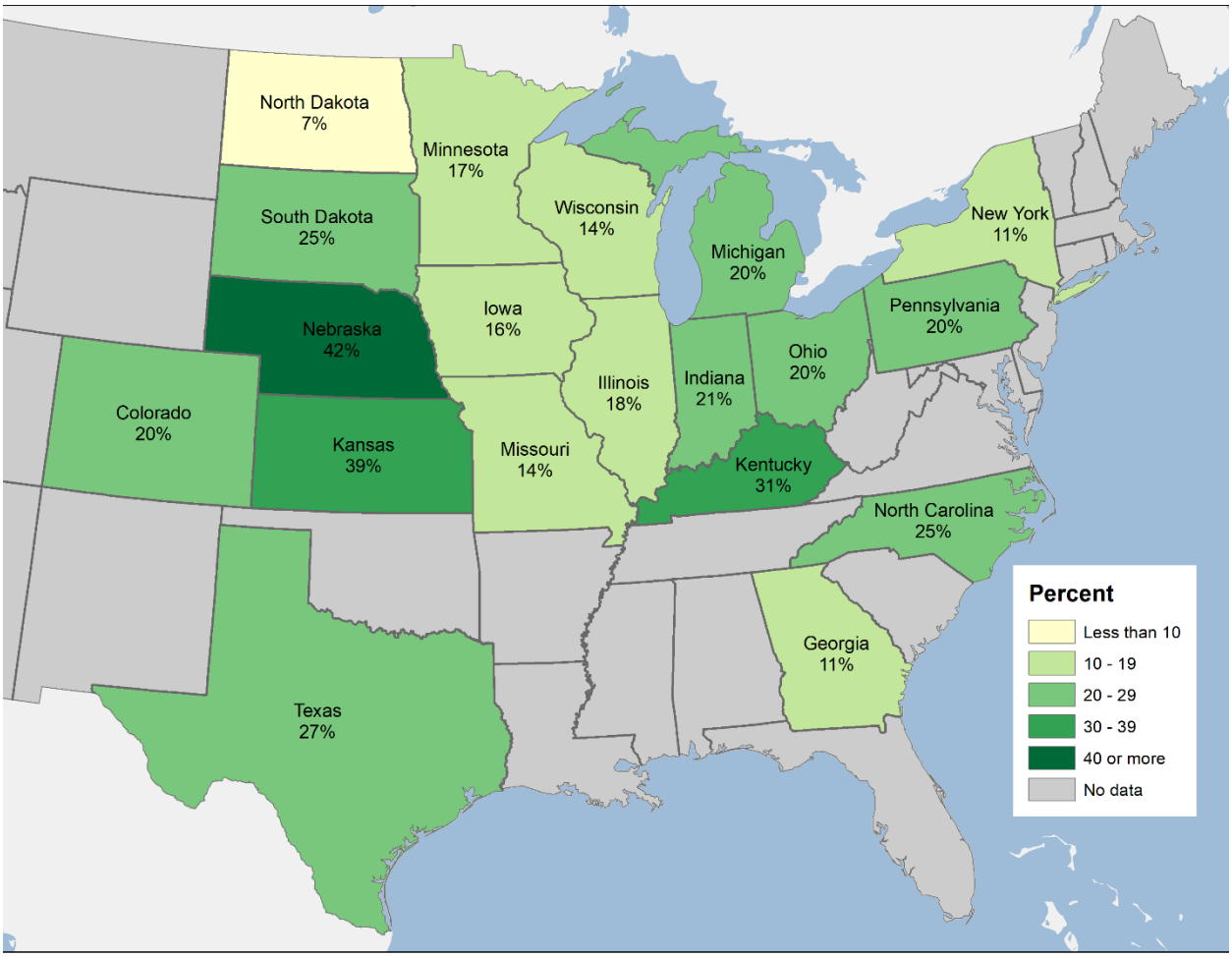


Figure 2: DT shares of U.S. state corn acreage, 2016. Note: In 2016, total U.S. corn acreage planted to DT varieties was 18.6 million acres. Source: USDA, Economic Research Service and National Agricultural Statistics Service, 2016 Agricultural Resource Management Survey.

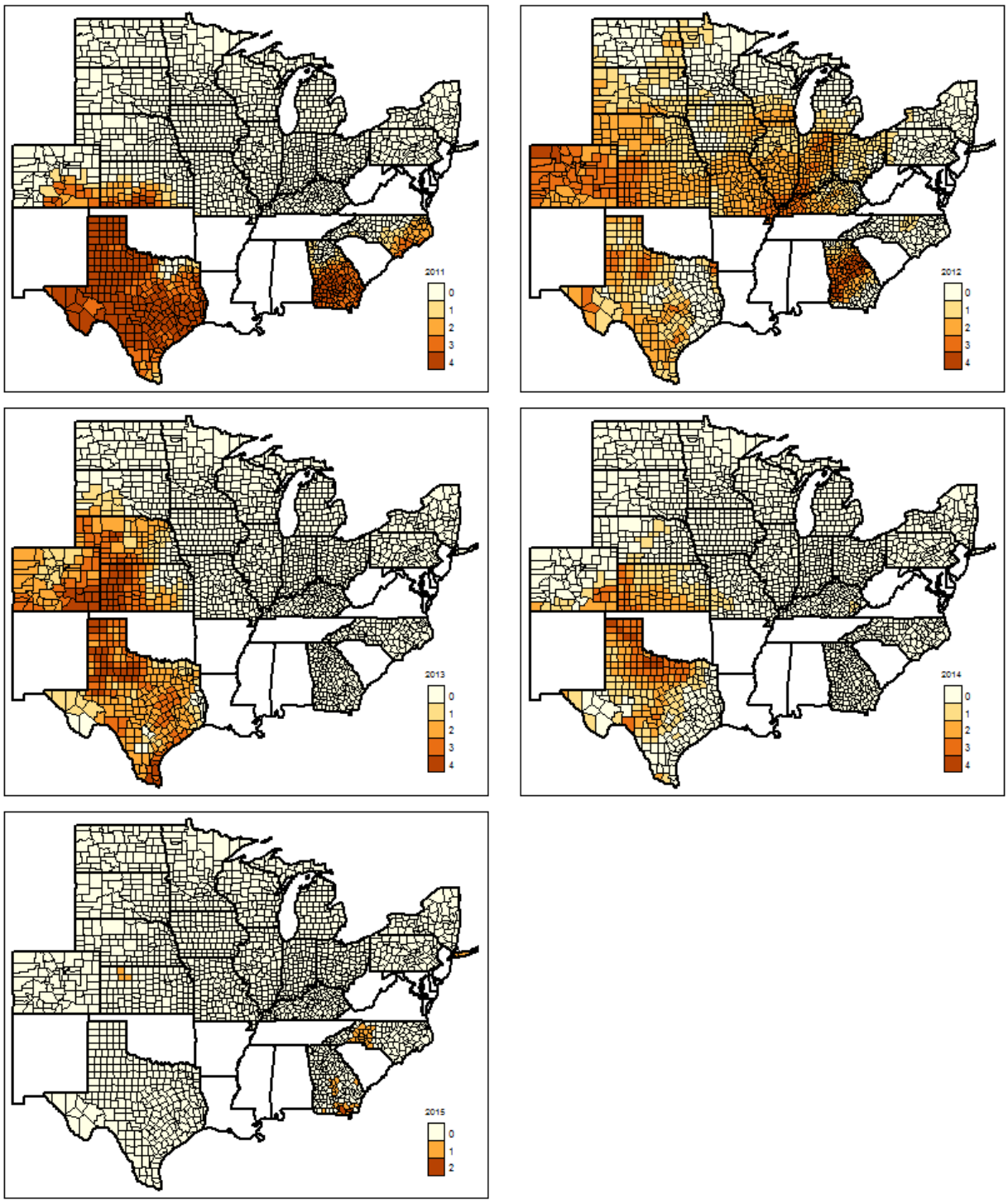


Figure 3: U.S. Drought Monitor index of droughts, 2011-15. Note: The U.S. Drought Monitor sorts drought into five categories: abnormally dry (a drought precursor, D0), moderate (D1), severe (D2), extreme (D3), and exceptional (D4). These can be thought of in terms of potential impacts: short-term dryness (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.

their long-run risk. These discrepancies in short-run exposure and long-run risk partially motivate our economic framework, which we discuss next.

3 Economic Framework

We define the farmer's partial per-acre profit function as

$$\pi_s = PY_s\left(DT; D_s\right) - P^{DT}DT, \tag{1}$$

where P represents the output price, Y_s is state-contingent production (corn yields), p^{DT} is the price premium of the DT corn seed technology, and $DT \in \{0, 1\}$ represents the binary decision to use DT seed varieties. Yields are a function of both drought-tolerant seed use and drought, Since seed decisions occur on or before planting time, DT seed use and the DT seed price premium are not state-contingent. We also assume that farmers do not consider output prices to be state-dependent. The farmer's objective is to maximize their evaluation of state-contingent profits, choosing whether or not to plant DT varieties

$$\max_{DT \in \{0,1\}} W\left(\boldsymbol{\pi}\right), \tag{2}$$

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 drought tolerant seeds if

$$W\left(\boldsymbol{\pi^1}\right) > W\left(\boldsymbol{\pi^0}\right), \tag{3}$$

where $\boldsymbol{\pi^1} = \boldsymbol{\pi}\left(DT = 1\right)$ and $\boldsymbol{\pi^0} = \boldsymbol{\pi}\left(DT = 0\right)$.

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 (e.g., prospect theory) and long-run drought risk (e.g., mean variance utility) influence farmers' economic decision making. Given that farmers' underlying preference

structures are unknown and difficult to determine empirically, we estimate regression specifications consistent with both models.[4]

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, 2019). We choose the mean variance model with preference function

$$W(\boldsymbol{\pi}) = v\left(\mu(\boldsymbol{\pi}), \sigma^2(\boldsymbol{\pi})\right). \tag{4}$$

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, $Y_s = \Upsilon d_s$ where Υd_s is drought-free yields and $d_s(.) \in \{0, 1\}$ is a "damage abatement" function that reduces yield losses due to drought, we can then choose a preference function such that

$$v^1 - v^0 = P\Upsilon \exp\left\{\mu[\pi_s^1(d_s)] - \mu[\pi_s^0(d_s)] - \left(\sigma[\pi_s^1(d_s)] - \sigma[\pi_s^0(d_s)]\right)\right\} - p^{DT}. \tag{5}$$

The preference function defines the marginal utility of DT seeds.[5] With this preference function a farmer will choose to use DT corn seed varieties if $v^1 - v^0 > 0$, i.e., if her utility from adopting these varieties exceeds her utility from not adopting them. Re-arranging this inequality and applying the logarithmic transformation implies that

$$\ln P + \ln \Upsilon + \mu[\pi_s^1(d_s)] - \mu[\pi_s^0(d_s)] - \left(\sigma[\pi_s^1(d_s)] - \sigma[\pi_s^0(d_s)]\right) > \ln p^{DT}. \tag{6}$$

[4] In earlier versions of this research that used drought severity indicators rather than monthly counts of droughts in each severity category, 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 very similar to those from reduced-form weighted probit regressions of adoption on the drought severity indicators.

[5] The preference function is increasing in output prices, drought free-yields, and mean drought-related yield loss reduction. The marginal utility of DT seeds is decreasing in the variance of drought-related yield loss reduction. 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.

If the mean of utility (of profits) from adopting DT seeds 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 (6) 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

$$\beta_0 + \beta\sigma_{PMDI} > \epsilon, \tag{7}$$

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

3.2 Prospect Theory

Expected utility models, while sometimes an improvement over expected profit maximization 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 plant DT corn. In some regions, severe or extreme drought is rare, but if some farmers attach substantial importance to a small number of these rare occurrences, their adoption rates could be systematically higher than those who do not over-weight such events.[6] For these reasons, we also use the following preference function

$$W(\boldsymbol{\pi}) = \sum_{s=1}^{S} h(\rho_s)u(\pi_s), \tag{8}$$

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 noting that the marginal rate of substitution

[6]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.

between two state-dependent profits is $MRS_{ss'} = \frac{u\left(\pi_s^1\right)-u\left(\pi_s^0\right)}{u\left(\pi_{s'}^1\right)-u\left(\pi_{s'}^0\right)} = \frac{\omega_s}{\omega_{s'}}$. This simplifies the preference function to

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

where $\omega(\cdot)$ is the probability-weighted marginal utility of profits. Farmers will adopt DT corn varieties if

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

This inequality is also true when multiplied by any constant k. Substituting in the production function, $Y_s = \Upsilon d_s$, farmers will adopt if

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

where $d_s^1 \in (0,1)$ is the percent of yields not reduced by drought when using DT seeds, and $d_s^0 \in (0,1)$ is the percent of yields not reduced by drought without DT seeds. We do not observe farmers' preference weights on state-dependent outcomes and probabilities when making their decisions. A common approach is to use the historically-observed states to proxy for the states that farmers face when making seed decisions. Here, we assume that farmers use their experience of realized states from previous years to form their set of possible states. States are defined according to the drought severity categories from the U.S. Drought Monitor such that

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

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, $\exp(\sum_{s=1}^{S} \sum_{t=1}^{T} kh(\rho_s)\omega_s \left(d_s^1 - d_s^0\right) D_{st})$.[7] Substituting this into (12) and applying a logarithmic transformation, we get the following inequality

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

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

This leads to an empirical equation that resembles

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

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 varietal adoption decisions.[8] 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.[9] We therefore estimate the model motivated from mean-variance preferences separately from the model motivated by prospect theory.

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 an indicator of field-level irrigation; and SL_i is a vector of field-level soil characteristics, land attributes, and corn basis from nearby grain elevators for February 2016.[10] 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

[8] 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.

[9] 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.

[10] Due to lack of sufficient drought variation across field locations, we are unable to include all year-severity drought combinations in specification (16). Relative to a base category of no drought, we are unable to include exceptional droughts (D4) in 2014 and extreme and exceptional droughts (D3-D4) in 2014.

probit regressions.[11]

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

$$DT_i = \alpha_0 + \sum_{s=0}^{4} \sum_{t=2011}^{2015} \alpha_{st} D_{st,i} + \alpha_{\overline{W}} \overline{W}_i + \alpha_{Irr} Irr_i + \alpha_{SL} SL_i + \epsilon_i, \tag{16}$$

where $D_{st,i}$ are counts of the number of months in which the field was located in an area with drought of severity s in year t.[12] We choose to use monthly counts of drought severity in place of severity indicators suggested by our motivating framework because this most closely aligns with other applied climate econometric studies that sum weather variables over time and then sort them into bins, like growing degree days above and below thresholds (e.g. Schlenker and Roberts, 2009; Burke and Emerick, 2016) or weeks of drought within severity categories (Kuwayama et al., 2019).

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

[11] 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).

[12] 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.

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 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 recently 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.[13] 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).

[13]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.

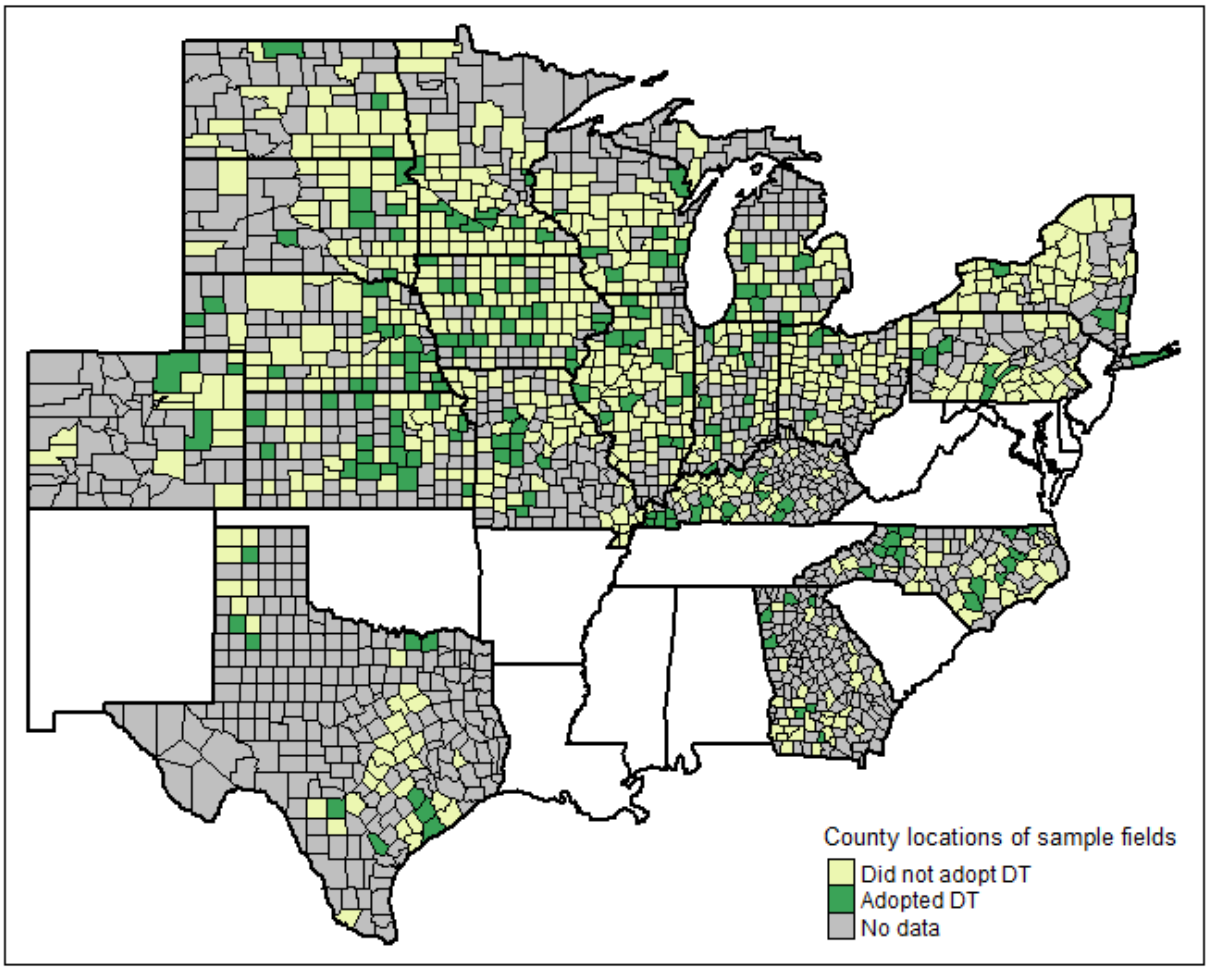


Figure 4: U.S. county adoption of DT corn, 2016. Note: All surveyed states in 2016 are depicted (Colorado, Georgia, Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, New York, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, Texas, and Wisconsin). Multiple 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.

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

The Agricultural Resource Management Survey (ARMS) is our primary source of data.[14] 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 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).[15] 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.[16] However, the U.S. Drought Monitor is

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

[15] 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).

[16] USDA uses the U.S. Drought Monitor as a guide to making disaster declarations and to help determine

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

	Units-Range	Sample Mean	Weighted Mean	Standard Error	Min	Max
2016 DT adoption rate	{0,1}	0.21	0.20	0.02	0	1
2011 months in D0	[0,12]	1.23	1.17	0.10	0	10
2011 months in D1	[0,12]	0.75	0.66	0.08	0	10
2011 months in D2	[0,12]	0.30	0.18	0.04	0	8
2011 months in D3	[0,12]	0.06	0.03	0.01	0	4
2011 months in D4	[0,12]	0.06	0.02	0.01	0	6
2012 months in D0	[0,12]	2.16	2.12	0.10	0	10
2012 months in D1	[0,12]	2.39	2.38	0.14	0	8
2012 months in D2	[0,12]	2.06	2.18	0.22	0	10
2012 months in D3	[0,12]	0.88	0.86	0.14	0	7
2012 months in D4	[0,12]	0.23	0.18	0.06	0	8
2013 months in D0	[0,12]	1.67	1.83	0.14	0	8
2013 months in D1	[0,12]	0.99	0.98	0.11	0	7
2013 months in D2	[0,12]	0.68	0.57	0.10	0	9
2013 months in D3	[0,12]	0.28	0.26	0.08	0	8
2013 months in D4	[0,12]	0.05	0.04	0.02	0	8
2014 months in D0	[0,12]	1.13	1.11	0.13	0	9
2014 months in D1	[0,12]	0.56	0.55	0.09	0	9
2014 months in D2	[0,12]	0.13	0.11	0.03	0	7
2014 months in D3	[0,12]	0.03	0.01	0.01	0	9
2015 months in D0	[0,12]	1.10	0.97	0.12	0	9
2015 months in D1	[0,12]	0.22	0.17	0.04	0	7
2015 months in D1	[0,12]	0.02	0.02	0.01	0	3
Drought risk	[0,∞)	2.27	2.26	0.03	1.60	3.08
30-year temp. mean	° Celsius	20.82	20.50	0.19	16.57	28.03
30-year temp. std. dev.	° Celsius	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
Clay	{0,1}	0.13	0.15	0.02	0	1
Irrigation x clay	{0,1}	0.01	0.004	0.002	0	1
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, ∞)	1.09	1.18	0.04	0	3.38
Average 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.

subject to expert review and revision, which could introduce noise and reduce comparability across locations. Our preferred measure is instead the number of annual months of drought within the Drought Monitor's severity classes, but based on the PMDI, also produced by NOAA.[17] To construct field-level values of monthly drought counts, 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), 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 (table 1). However, nearly two-thirds of fields experienced a severe or extreme drought at some point in 2012. On average, there were 2.4 months of moderate drought (D1) and 2.1 months of severe drought (D2) for our sample 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. Similarly, many of the fields were at risk of experiencing a drought in any given year; the weighted mean of the standard deviation of long-run PMDI was 2.26.

Yearly temperature and precipitation are taken from Oregon State University's PRSIM 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

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.

[17]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).

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 (May-August) 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).

Field-level indicators of irrigation use, clay-dominant soils, and highly-erodible land are taken from the ARMS data. 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). 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. 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.[18] 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.

National seed premiums for DT corn variety traits are roughly $10 per bag of 80,000 seeds (McFadden et al., 2019). Although some evidence suggests that DT seed premiums

[18]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.

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.[19] The weighted average basis in our sample is -$0.15.

5 The Role of Weather 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 estimate. Last, we present an illustrative counterfactual analysis by asking how 2016 DT adoption rates would have evolved in the absence of certain drought-years and combinations of drought years.

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 10.4 percentage points, a large but insignificant effect.[20] Thus, long-run drought risk does

[19]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.

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

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 two percentage points. Irrigation has a significant main-level effect with the expected negative sign, and its impact on adoption is 41 percentage points higher on fields with primarily clay soils. Similarly, operators of fields that are of inherently lower lower productivity—those that are highly erodible and have greater variability in suitability for growing corn—are more likely to have planted DT varieties in 2016.

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 0.195 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 sharply positive and significant at the 1% 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 deteriorates. The 30-year temperature average and precipitation variability increase the probability of adoption, with the latter having a large 13.4-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 important distinction is that our study relies on weather, climate, and adoption data at a much finer spatial scale than county-level analyses.

As expected, the average marginal effects from the probit model (columns 1b-3b) are 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 one percentage point, on average. Given that our focus is on identification of weather 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 observation in this model.

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

	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	0.104	0.195**		0.102	0.195***	
	(0.074)	(0.075)		(0.074)	(0.010)	
30-year temp. mean	0.023**		0.026**	0.023**		0.026**
	(0.011)		(0.010)	(0.010)		(0.010)
30-year temp. std. dev.	0.107		0.170	0.139		0.195
	(0.213)		(0.205)	(0.205)		(0.199)
30-year precip. mean	−0.071		−0.094	−0.067		−0.091
	(0.058)		(0.058)	(0.058)		(0.057)
30-year precip. std. dev.	0.098		0.134*	0.090		0.128*
	(0.080)		(0.079)	(0.080)		(0.077)
Irrigation	−0.075*	−0.048	−0.062	−0.065*	−0.047	−0.055
	(0.042)	(0.037)	(0.040)	(0.034)	(0.034)	(0.034)
Clay	0.011	0.011	0.008	0.010	0.010	0.008
	(0.037)	(0.039)	(0.037)	(0.036)	(0.035)	(0.037)
Irrigation x clay	0.413*	0.408*	0.429*	0.400*	0.400*	0.420*
	(0.217)	(0.211)	(0.219)	(0.225)	(0.221)	(0.224)
Highly erodible	0.071*	0.077**	0.073*	0.069*	0.075**	0.071*
	(0.037)	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)
Corn-soy soil index mean	−0.006	−0.000	−0.006	−0.005	−0.000	−0.005
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)
Corn-soy soil index std. dev.	0.016	0.019	0.006	0.016	0.018	0.007
	(0.027)	(0.027)	(0.025)	(0.027)	(0.027)	(0.025)
February 2016 basis	0.074	0.109**	0.050	0.086	0.111**	0.061
	(0.082)	(0.048)	(0.082)	(0.081)	(0.049)	(0.080)
Constant	−0.556	−0.253	−0.433			
	(0.387)	(0.183)	(0.370)			
Observations	1,768	1,768	1,768	1,768	1,768	1,768
Correctly classified (%)	79	79	79	79	79	79
F-statistic	2.38	2.89	2.29	2.50	2.99	2.47
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.

The duration, severity, and recentness of droughts also significantly affect seed technology adoption (table 3). There are two important features of these results. First, for any year, the probability of adoption is generally increasing in the number of annual months across drought severity categories for which there are ample data. In particular, uptake is monotonic in drought severity at lower severity levels (D0-D1 or D0-D1-D2) for years 2011-13 and 2015. That is, point estimates are negative, zero, and then positive for years 2011 and 2013 (D0-D1-D2), negative and then positive for 2012 (D0-D1), and zero and then positive for 2015 (D0-D1). Second, our results are consistent with the economics literature showing that drought has impacts on agricultural outcomes above and beyond those of just precipitation and temperature (columns 1a and 1b). Although climatic effects of temperature and rainfall explain most variation in yields (e.g. Kuwayama et al., 2019), a significant role remains for drought when explaining farmers' choices of new seed varieties.

Relative to areas in which there was no drought, an additional month of extreme drought (D3) in 2013 increased 2016 adoption by 8.6 percentage points. In contrast, an additional month of extreme or exceptional drought (D4) in other years (e.g., 2011-12 and 2014) either *reduces* the probability of adoption or has no significant effect. The negative relationship could be indicative of farmers' understanding that drought tolerance does not pay (e.g., do not yield significantly higher than non-DT varieties) under very severe conditions (McFadden et al., 2019). The null relationship could partly arise from relatively less variation in the D3 and D4 data (table 1).

Consistent with expectations, increased average temperatures and variability of rainfall lead to higher adoption, as does the presence of highly erodible land. Increased rainfall leads to lower adoption. The point estimates for irrigation are 3-4 percentage points larger than those for the mean-variance model, though its effects are not moderated by the dominance of clay in the topsoil profile (table 3, columns 1a and 1b). This suggests that irrigation could be increasingly important under changing long-term climate conditions.

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

	LPM (marginal effects)		Probit (average marginal effects)	
	(1a) Drought shocks & climate	(2a) Drought shocks only	(1b) Drought risk & climate	(2b) Drought risk only
2011 months in D0	−0.022**	−0.015*	−0.023**	−0.016*
2011 months in D1	−0.020	−0.017	−0.019	−0.016
2011 months in D2	0.047***	0.053***	0.040***	0.048***
2011 months in D3	−0.044	−0.022	−0.038	−0.014
2011 months in D4	0.047	0.038	0.047	0.037
2012 months in D0	−0.018**	−0.016*	−0.018**	−0.017*
2012 months in D1	0.016*	0.015*	0.015*	0.015*
2012 months in D2	−0.007	−0.005	−0.006	−0.005
2012 months in D3	−0.040***	−0.042***	−0.039***	−0.041***
2012 months in D4	−0.024	−0.018	−0.021	−0.016
2013 months in D0	−0.007	−0.001	−0.005	−0.008
2013 months in D1	0.002	−0.002	0.003	−0.0005
2013 months in D2	0.028*	0.029*	0.023*	0.024*
2013 months in D3	0.086***	0.082**	0.079***	0.075**
2013 months in D4	0.056	0.042	0.051	0.039
2014 months in D0	0.018*	0.029***	0.014*	0.025***
2014 months in D1	−0.011	0.004	−0.011	0.003
2014 months in D2	0.019	0.028	0.021	0.026
2014 months in D3	−0.091*	−0.071	−0.089*	−0.068
2015 months in D0	0.001	−0.005	0.001	−0.006
2015 months in D1	0.048**	0.038*	0.044**	0.034*
2015 months in D2	−0.085	−0.120*	−0.066	−0.096*
30-year temp. mean	0.019*		0.019*	
30-year temp. std. dev.	−0.165		−0.149	
30-year precip. mean	−0.102*		−0.094	
30-year precip. std. dev.	0.163*		0.147*	
Irrigation	−0.116**	−0.087**	−0.097***	−0.080**
Clay	0.013	0.012	0.014	0.013
Irrigation x clay	0.349	0.354	0.319	0.328
Highly erodible	0.074**	0.080**	0.070*	0.076**
Corn-soy soil index mean	0.003	0.005	0.003	0.005
Corn-soy soil index std. dev.	0.017	0.016	0.014	0.012
February 2016 basis	0.016	0.064	0.023	0.069
Constant	0.137	0.162**		
Observations	1,768	1,768	1,768	1,768
Correctly classified (%)	78	78	79	78
F-statistic	6.02	5.72	5.40	5.13
R-squared	0.08	0.07		

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. For the two sets of LPM estimates, predicted probabilities were negative for 36 and 24 fields (respectively), and these predicted probabilities exceeded one for exactly one field. 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.

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.[21] 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 and five years, the range of the absolute value of the coefficients of variation for the drought severity counts is (14, 206). Variability in the 30-year climate regressors is lower, with the coefficients of variation ranging in (19, 119). Clay content, its interaction with irrigation, the corn-soy soil productivity index, and basis have among the least variation in the differenced data, suggesting that these measures are highly site specific.

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 less than 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 whose closest other fields are 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.

[21] 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.

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
Drought risk	0.001	0.065	0.002	0.052	−0.002	0.038
30-year temp. mean	−0.003	0.356	−0.003	0.276	0.008	0.205
30-year temp. std. dev.	0.001	0.022	0.001	0.020	0.001	0.019
30-year precip. mean	−0.003	0.114	−0.003	0.100	0.002	0.096
30-year precip. std. dev.	−0.003	0.090	−0.002	0.079	0.001	0.073
2011 months in D0	0.011	0.837	0.008	0.787	0.026	0.624
2011 months in D1	0.004	0.624	−0.003	0.599	0.005	0.424
2011 months in D2	−0.019	0.525	−0.002	0.505	0.021	0.410
2011 months in D3	−0.007	0.217	−0.003	0.233	0.005	0.218
2011 months in D4	−0.001	0.071	−0.002	0.067	0	0.073
2012 months in D0	0.013	0.951	−0.018	0.899	−0.005	0.841
2012 months in D1	0.071	1.060	0.048	0.980	0.013	0.864
2012 months in D2	−0.009	1.113	0.020	1.001	0.024	0.917
2012 months in D3	−0.003	0.871	0	0.816	−0.013	0.807
2012 months in D4	−0.017	0.475	−0.011	0.441	−0.013	0.286
2013 months in D0	0.031	1.039	0.038	0.942	0.034	0.893
2013 months in D1	0	0.946	0.011	0.783	−0.024	0.687
2013 months in D2	−0.008	0.758	−0.026	0.587	−0.008	0.381
2013 months in D3	0.003	0.527	0.002	0.413	−0.008	0.381
2013 months in D4	0.001	0.182	0.003	0.174	0	0.145
2014 months in D0	−0.062	1.053	−0.072	0.918	−0.032	0.853
2014 months in D1	0.002	0.786	−0.005	0.646	−0.026	0.665
2014 months in D2	0.002	0.385	−0.002	0.308	−0.008	0.286
2014 months in D3	0.002	0.100	−0.002	0.039	−0.003	0.051
2015 months in D0	0.059	1.027	−0.060	0.878	−0.011	0.666
2015 months in D1	−0.001	0.440	0.002	0.358	−0.013	0.344
2015 months in D2	0.004	0.161	0.002	0.140	−0.003	0.154
Irrigation	0.006	0.241	0.006	0.246	0.011	0.229
Clay	−0.011	0.460	−0.036	0.451	−0.061	0.458
Irrigation x clay	−0.002	0.078	−0.006	0.077	−0.011	0.102
Highly erodible	0.002	0.439	0.008	0.448	0.008	0.445
Corn-soy soil index mean	−0.006	0.078	−0.009	0.071	−0.008	0.064
Corn-soy soil index std. dev.	−0.0001	0.041	−0.001	0.040	−0.0005	0.038
February 2016 basis	0.001	0.041	−0.0003	0.029	0.001	0.022

Note. For all regressors except the two soil index variables and February 2016 basis, the sample sizes are the following: 999 fields (mi. < 14), 664 fields (mi. < 9), and 380 fields (mi. < 6). Samples sizes for the two soil index variables are 995 fields (mi. < 14), 662 fields (mi. < 9), and 378 fields (mi. < 6). February 2016 basis data are available for 1,021 fields (mi. < 14), 671 fields (mi. < 9), and 395 fields (mi. < 6).

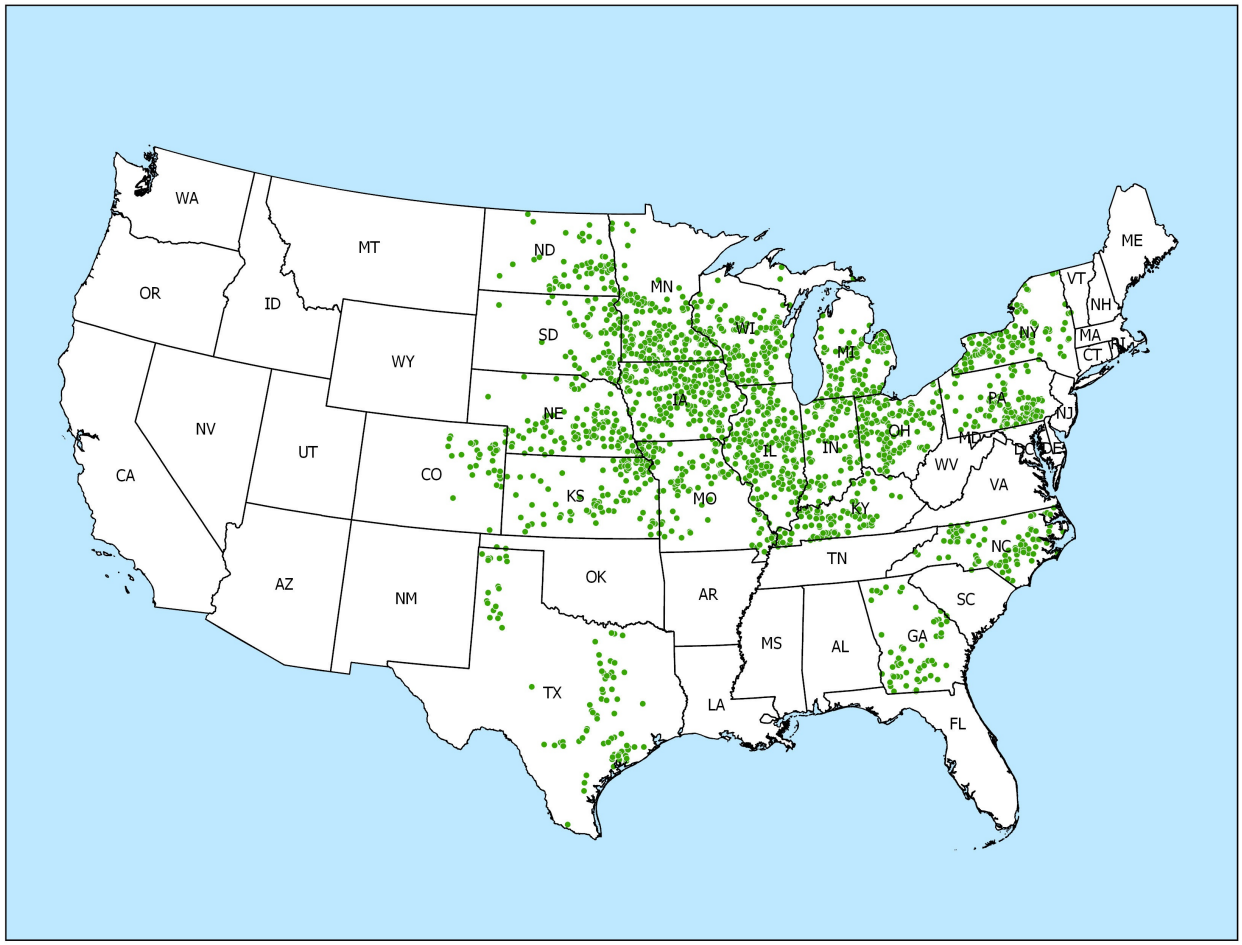


Figure 5: Surveyed fields' locations, 2016. Note: To preserve privacy and meet USDA data disclosure requirements, dots representing field locations are disproportionately large relative to map scale. Source: USDA, Economic Research Service and National Agricultural Statistics Service, 2016 Agricultural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

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 (995, 662, and 378 fields), with an accompanying decline in the models' degrees of freedom. For purposes of comparison, we 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 1400, 1001, and 616 observations, respectively). As in the LPM and probit results, all standard errors have been clustered at the level of USDA's crop reporting districts.[22]

For the SFD model estimated at the 14-mile distance, fewer of the drought severity months are significant (table 5, column 1a) relative to the levels estimation (1b). At this distance, it is unclear whether or not the location fixed effect has been completely differenced out, while the model is estimated with fewer observations—and that exhibit less variation. Nonetheless, there is still evidence of a weak within-year monotonic effect of drought severity in 2011 (D0-D1-D2) and 2012 (D0-D1). This effect is somewhat larger in the levels model for the D0, D1, and D2 categories in 2011. Regarding other attributes, irrigation and the presence of highly erodible land are no longer significant. The corn-soy soil productivity index is now significant at the 1% level and suggests that, relative to fields which are completely unsuitable for growing corn, DT varieties are adopted at rates that are 79 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 different from those obtained in the 14-mile sample (1a), as well as level estimates at the 9-mile threshold (2b). We observe increases in the marginal effects across severity categories in 2011 (D0, D1, D2) and 2012 (D0, D1), but these point estimates are largely insignificant. In the levels model, monotonic effects are also apparent in these years, in addition to 2013 (D2-D3-D4) and 2015 (D0-D1). There is broad consistency in the signs

[22]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 divided into nine adjacent CRDs. Clustering at this level is designed to mitigate the effects of spatial autocorrelation in the econometric errors.

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

	Mi. < 14		Mi. < 9		Mi. < 6	
	(1a) SFD	(1b) Levels	(2a) SFD	(2b) Levels	(3a) SFD	(3b) Levels
2011 months in D0	−0.037	−0.022*	−0.007	−0.027*	0.131*	−0.035**
2011 months in D1	−0.022	−0.023	0.040	−0.008	0.089	−0.016
2011 months in D2	0.143**	0.058**	0.171*	0.033	0.301**	−0.001
2011 months in D3	−0.157*	−0.094	−0.272	−0.165**	0.380*	−0.133
2011 months in D4	−0.088	0.047	−0.164	0.201**	0.924**	0.223
2012 months in D0	0.020	−0.021**	0.022	−0.020*	0.067	−0.017
2012 months in D1	0.041*	0.013	0.054	0.006	0.081	0.020
2012 months in D2	0.016	−0.012	−0.022	0.003	−0.042	0.009
2012 months in D3	−0.066	−0.038***	−0.098*	−0.057***	−0.180*	−0.048**
2012 months in D4	−0.044	−0.034	−0.014	−0.061**	0.006	−0.086*
2013 months in D0	−0.031	−0.005	−0.069*	−0.005	−0.151***	−0.017
2013 months in D1	0.004	0.009	−0.076*	0.005	−0.218***	0.011
2013 months in D2	0.035	0.036**	0.009	0.036*	−0.098	0.029
2013 months in D3	0.063	0.064	0.091	0.090**	0.038	0.101
2013 months in D4	−0.061	0.079	−0.021	0.153**	−2.619**	0.210**
2014 months in D0	0.013	0.008	0.049	0.007	0.042	0.002
2014 months in D1	−0.008	−0.018	0.072	−0.046**	0.136	−0.027
2014 months in D2	0.011	0.001	−0.022	0.031	−0.053	−0.033
2014 months in D3	−0.140	−0.063	0.142	−0.239***	−0.876	−0.275**
2015 months in D0	0.005	0.0003	0.041	−0.008	−0.053	−0.015
2015 months in D1	−0.030	0.057*	−0.099	0.083**	0.038	0.085*
2015 months in D2	0.239	−0.057	0.059	−0.094	2.572**	−0.143
30-year temp. mean		0.028***		0.029**		0.042**
30-year temp. std. dev.		−0.026		−0.004		−0.083
30-year precip. mean		−0.055		−0.087		−0.014
30-year precip. std. dev.		0.157		0.189		0.094
Irrigation	−0.117	−0.163***	−0.111	−0.175***	−0.083	−0.167**
Clay	−0.083	−0.022	−0.105	−0.043	−0.206**	−0.020
Irrigation x clay	0.404	0.492*	0.372	0.524*	0.543	0.564*
Highly erodible	0.070	0.051	0.115*	0.094**	0.032	0.002
Corn-soy soil index mean	0.793***	−0.014	0.442**	−0.067	0.364	−0.094
Corn-soy soil index std. dev.	0.490	0.067	−0.067	0.081	0.203	0.315
February 2016 basis		0.030		0.014		−0.049
Constant	−0.023	−0.369	−0.011	−0.311	−0.010	−0.639
Observations	995	1,400	662	1,001	378	616
Correctly classified (%)	80	79	80	78	81	79
R-squared	0.07	0.07	0.08	0.09	0.20	0.10
Clusters	121	116	107	104	99	93

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. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.

and sizes of the soil coefficients between (1a) and (2a), though the relatively larger effect of erosion is more precisely estimated in (2a). As in the previous estimation at the 14-mile threshold, there are increasing discrepancies between the SFD and level estimates. This is somewhat similar to the Druckenmiller and Hsiang (2018) finding that marginal effects of soil variables are highly sensitive to how the spatial first differences are constructed.

Many of the SFD point estimates are significant for fields with neighboring observations that are at a distance of 6 miles or less (3a). The same broad monotonic pattern in the estimates for (1a) and (2a) hold for years 2011 and 2015. However, the point estimates of the monthly drought counts are significantly larger in absolute value than those of (1a) and (2a). By differencing out potentially bias-inducing spatial fixed effects, the impacts of the short-run drought shocks are magnified. The substantially smaller sample size, though, is contributing to some of the implausibly large coefficients (e.g., D4 in 2011).[23]

5.3 Illustrative Counterfactual Analysis

To simulate the effects that recent droughts had on expected adoption of DT corn in 2016, we begin with the SFD and level LPM estimates from table 5. For both models across the three distances, we simulate the impacts of removing all single-year instances of drought between 2011 and 2015. We also examine what might have happened to 2016 DT corn adoption had there been no particularly severe instances of drought in 2011-13. We also analyze the potential impacts of removing all instances of drought in the most recent two sample years.

The simulations are carried out by setting all of the months in the particular year's D0-D4 drought severity categories to zero (meaning that all months in the particular year are implicitly drought-free) and then examining the summary statistics of the fitted probabilities. The simulations for decreased exposure show few significant decreases in 2016 adoption rates from the SFD estimates (table 6). We find from the 14-mile threshold model that, had droughts not occurred at all in any single year, expected DT seed adoption in 2016 would have generally been within $\pm$ 1 percentage point of current levels, but these are insignificant.

[23]Given the novelty of the spatial first differences approach, the consequences of restricting samples to observations that could be "too close" (e.g., using other measures of spatial dependence, like Moran's I) have not been fully explored.

Table 6: Counterfactual Effects of Historical Droughts on the Probability of Drought-Tolerant Variety Adoption

	Mi. < 14		Mi. < 9		Mi. < 6	
	(1a) SFD	(1b) Levels	(2a) SFD	(2b) Levels	(3a) SFD	(3b) Levels
No 2011 drought	0.019	0.025***	−0.047	0.029***	−0.064	0.045***
	(0.031)	(0.002)	(0.040)	(0.003)	(0.079)	(0.005)
No 2012 drought	−0.102	0.073***	−0.058	0.075***	−0.111	0.023***
	(0.087)	(0.002)	(0.099)	(0.003)	(0.102)	(0.005)
No 2013 drought	0.018	−0.024***	−0.099**	−0.009***	0.102	0.004
	(0.029)	(0.002)	(0.046)	(0.003)	(0.099)	(0.004)
No 2014 drought	−0.005	0.002	−0.033	0.010***	−0.011	0.011***
	(0.016)	(0.002)	(0.037)	(0.003)	(0.057)	(0.004)
No 2015 drought	−0.004	−0.012***	−0.014	−0.009***	0.014	−0.031***
	(0.016)	(0.001)	(0.031)	(0.002)	(0.057)	(0.004)
No 2011-13 droughts	−0.077	0.058***	−0.004	0.060***	−0.188	0.035***
	(0.095)	(0.003)	(0.121)	(0.004)	(0.153)	(0.006)
No 2014-15 droughts	−0.008	−0.010***	−0.041	0.001***	−0.001	−0.020***
	(0.021)	(0.002)	(0.049)	(0.003)	(0.070)	(0.004)

Note. Each cell denotes the change in percentage points under the counterfactual indicated in each row. The baseline predicted probabilities for the LPM models are 21.1% (1b), 20.7% (2b), and 20.2% (3b). Standard errors are bootstrapped with replacement according to a base expansion factor using *B=1,000* bootstrap samples. Significance is denoted as ***p<0.01 and **p<0.05.

If important unobserved heterogeneity is more likely to be accounted for at shorter distances, then drought shocks have a potentially larger role to play on adoption for fields that are very close to other fields. This effect is evidenced by comparing estimates from (1a) with (2a) and (3a): the effects of drought on uptake become increasingly larger in absolute value, on average. At the 9-mile threshold, the SFD estimates suggest that 2016 adoption rates would have been 9.9 percentage points lower in the absence of the 2013 drought that adversely affected South Dakota, Nebraska, Kansas, Texas, and Colorado.

For the level estimates, the simulated change in adoption rates are in line with expectations from model estimates. Unlike those from the SFD estimates, though, the simulated probabilities from the levels models contain less variation across bootstrap samples, resulting in a greater fraction of significant predictions—and at lower significance levels. Although our SFD-based predictions are imprecise, they give far more plausible (negative) counterfactual effects. Many of the potentially-biased predictions from the levels model suggest that 2016 adoption would have been 1-8 percentage points *higher* had droughts in 2011-15 not occured.

Note, however, that these simulated counterfactuals should be interpreted with caution since LPMs can produce fitted probabilities less than zero and greater than one.[24]

5.4 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 over the coming years, our analysis suggests that 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

[24] Across the six models, several of the predicted probabilities did not lie in {0,1}. As such, we have discarded these predictions in the calculations of means and standard errors we report. However, our results are broadly robust to their inclusion.

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.[25]

6 Conclusions

Controlling for average weather conditions and the severity, recentness, and frequency of droughts, in addition to potentially-confounding location fixed effects, we find that exposure to drought during 2011-14 contributed to increased adoption in 2016, with greater severity generally leading to greater DT corn use. Adoption is also increasing in long-run drought risk, as measured by the standard deviation of the PMDI measure. Simulated probabilities suggest that current national uptake of drought-tolerant varieties would have been three percentage points lower, on average, had widespread drought not occurred between 2011 and 2013.

There are two main caveats of this research. First, 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 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,

[25]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.

Chavas, and Stiegert, 2010).[26] Second, although our counterfactual analysis provides some illustrative evidence about how uptake of drought-tolerant crop varieties could evolve under climate change, it should not be considered an approximation to an analysis of uptake as an adaptation mechanism. 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 prime area for further research is a causal analysis of how weather shocks impact drought-tolerant corn yields and net returns relative to non-DT yields and net returns. 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.

[26] 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.

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