Supplementary Information for "Weather, Climate, and Technology Adoption: An Application to Drought-Tolerant Corn in the United States," Jonathan McFadden, David J. Smith, Steven Wallander. In *American Agriculture, Water Resources, and Climate Change*, edited by Gary D. Libecap and Ariel Dinar. University of Chicago Press, 2023. https://www.nber.org/books-and-chapters/american-agriculture-water-resources-and-climate-change

This supplementary information document contains three appendices. Appendix A contains an overview of information (e.g., source, level of aggregation, and description) about the primary data used in the analysis, as well as a figure illustrating the spatial location and scale of the weather stations underlying our drought data. Appendix B discusses empirical challenges regarding use of seasonal or sub-seasonal drought forecasts as control variables in this analysis. Appendix C provides information on the extent of potential spatial variation in U.S. drought-tolerant (DT) corn prices.

Appendix A Data Overview

Table A1 Data Sources

Variable and units	Data Source	Area	Description
2016 DT corn adoption rate, {0,1}	ARMS	Field	Field planted to corn traited with drought resistance in 2016
Months of severe-or-worse droughts in 2011-15[1]	PMDI, USDM	12 nearest stations within 100 mi of field	Total number of months of D2 (severe), D3 (extreme), or D4 (exceptional) droughts in the growing season (May-September) during 2011-15, based on mapping Palmer Modified Drought Index (PMDI) to Drought Monitor (USDM) classes
Maximum drought value in 2011-15	PMDI	12 nearest stations within 100 mi of field	Maximum monthly PMDI value during 2011-15. (Note: to ease interpretation, we reverse the sign of the raw PMDI values so that larger positive numbers indicate greater drought severity.)
Drought risk, [0, ∞)	PMDI	County	Standard deviation of Palmer Modified Drought Index (PMDI) in July months over 1913-2013
30-year temperatures – mean and standard deviation, (° C)[2]	PRISM	4 km cells averaged to county	Average monthly temperature in corn growing season (May-August), averaged over 1985-2014.
30-year precipitation – mean and standard deviation, (in.)[2]	PRISM	4 km cells averaged to county	Average monthly temperature in corn growing season (May-August), averaged over 1985-2014.
Irrigation, {0,1}	ARMS	Field	Corn in any part of the field received irrigation in 2016
Share of irrigated, harvested corn acreage, [0,1]	Ag Census	County	Share of county's harvested corn acreage irrigated in 2012
Clay, {0,1}	ARMS	Field	Primary soil type for the field is clay
Highly erodible, {0,1}	ARMS	Field	Any part of field has been classified as USDA-NRCS as "highly erodible"
Corn-soy soil index – mean, [0,10] and standard deviation, [0, ∞)[3]	gSSURGO	30 m cell avg. within 3 km of field	USDA-NRCS' NCCPI about the soil's capacity for corn and soybeans
Average basis, ($)[4]	USDA, CME	5 nearest buyers within 70 mi of field	February 2016 cash price (within 70 mi of ARMS field) subtracted from March (national) futures price for the December 2016 contract traded on CME

Note. 1. Interpolation relies on inverse distance weighting (IDW) such that stations closer to sample fields receive greater weight than more distant stations. Only U.S. Drought Monitor (USDM) categories are used; county PMDI index values are matched to USDM categories.
2. Aggregation to county is based on distance to centroids, clipped and weighted by cropland density.
3. Average NCCPI values are first aggregated by NRCS to 30 m cells; we use an average of all cells within 3 km of the field.
4. Interpolation relies on IDW such that grain purchasers closer to sample fields receive greater weight than more distant purchasers.

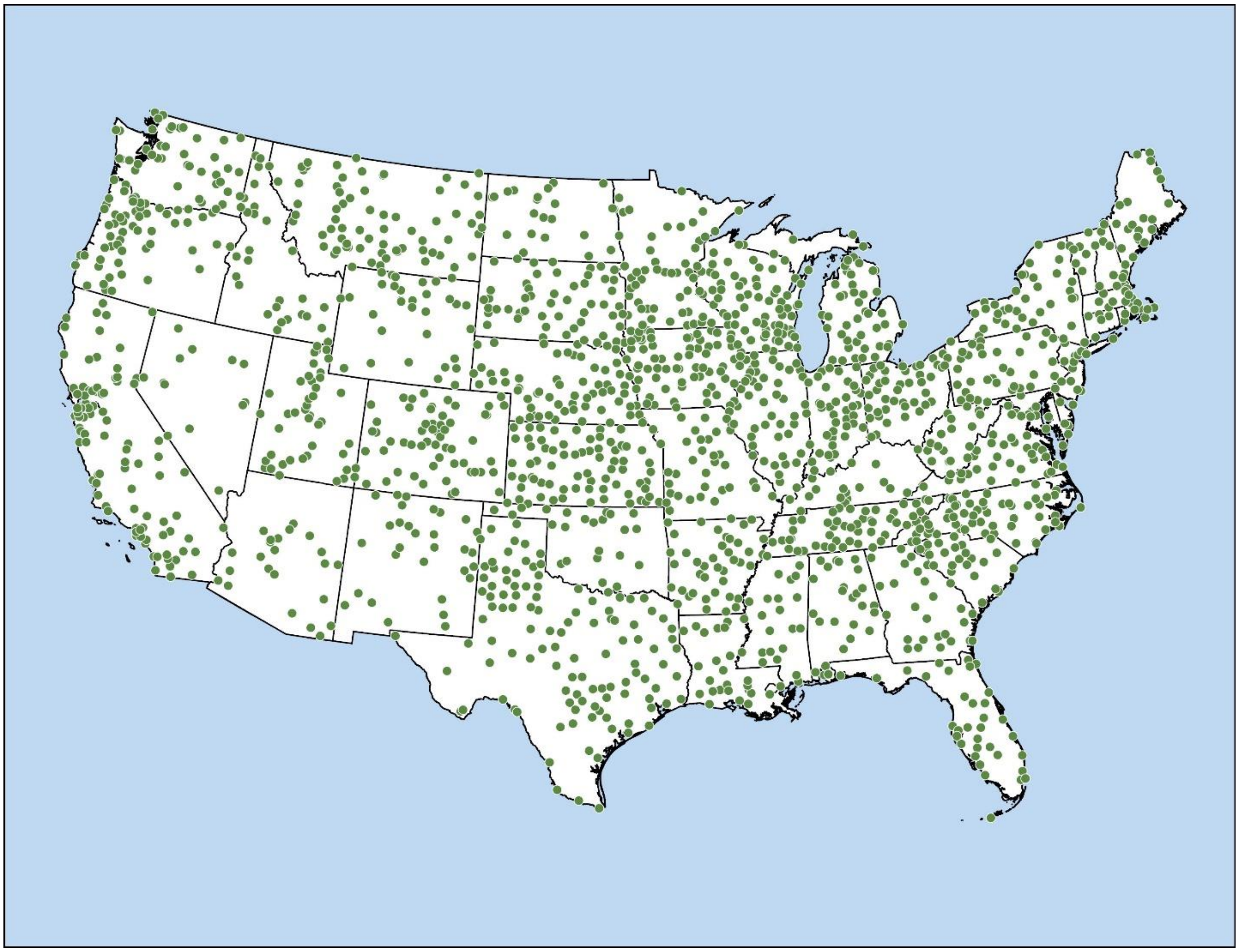

Figure A1. Locations of weather stations underlying PMDI data.

Figure A1 depicts the coordinates of the roughly 1,815 weather stations across the contiguous United States that provide input into calculations of NOAA's Modified Palmer Drought Severity Index (PMDI). Although aggregation bias arising from use of gridded weather and climate data can be problematic in some climate change analyses, our use of interpolation based on inverse distance weighting (IDW) from the corn field to 12 nearest weather stations alleviates these concerns (e.g., Auffhammer et al., 2013). This is because the IDW-based interpolation generates variation in the main coefficients of interest—monthly counts of drought severity—while giving more weight to index values that are more likely to hold at fields in our sample. Although there is fewer than one weather station per county (fig. A1), significant aggregation bias is unlikely to hold given the density of our sample points (fig. 5, main text) and the fact that drought conditions, unlike precipitation events that can be highly localized, tend to pervade across wide geographic areas (e.g., Cook et al., 2015).

Appendix B Drought Forecasts

Recent studies have shown that omitted variables bias can arise from excluded expectations of future weather when estimating the impacts of climate on agricultural land values using cross-sectional data (Severen et al., 2018) and the impacts of weather shocks on broader economic outcomes (Lemoine, 2017). Empirical models that do not account for agents' forecasts (or use of forecasts) of changing weather conditions can produce skewed climate change predictions if optimal decisions depend on such forecasts. Apart from those in models of agricultural land values, seasonal weather forecasts could influence U.S. crop farmers' economic decision making about crop choice and irrigation use, among other input decisions.

The Climate Prediction Center at NOAA's National Weather Service produces Monthly Drought Outlook (MDO) and Seasonal Drought Outlook (SDO) forecasts. The latter are generally valid for the three months beyond release date. Both datasets provide illustrations of large-scale trends using subjective probabilities of droughts from statistical and dynamic forecasts (NOAA, 2019a; NOAA, 2019b).[1] Geographical summaries of four categories of drought changes are supplied: 1) persists, 2) remains but improves, 3) removal unlikely, and 4) development likely—all based on the U.S. Drought Monitor's D1-D4 classifications.

There was virtually no variation in the MDO or SDO forecast data at the time farmers were making their corn varietal decisions in 2016 for our study region (figs. B1-B6). Drought was expected to persist during February, March, and April 2016 for several areas in the Pacific Northwest and American Southwest (fig. B1), though these areas were not surveyed in the 2016 ARMS because their estimated corn acreage was eclipsed by at least 19 other states included in the survey. Early-season forecasts are similar: the vast majority of the contiguous U.S. and also major corn-producing areas did not have drought and were not forecast to develop drought within the relevant timeframe (fig. B2). In contrast, widespread droughts in California, Oregon, Nevada, and Utah were forecast to remain but improve.

Lack of adequate variation in short-term drought forecasts generally precludes us from estimating a model that conditions farmers' adoption decisions on these kinds of forecasts.

[1] To the extent that these subjective probability models rely extensively on near-term U.S. Drought Monitor data and climatology, our use of the number of months within drought categories, as well as the first two moments of the 30-year distributions of temperature and rainfall, is expected to capture most of the effect, if any, of seasonal drought forecasts.

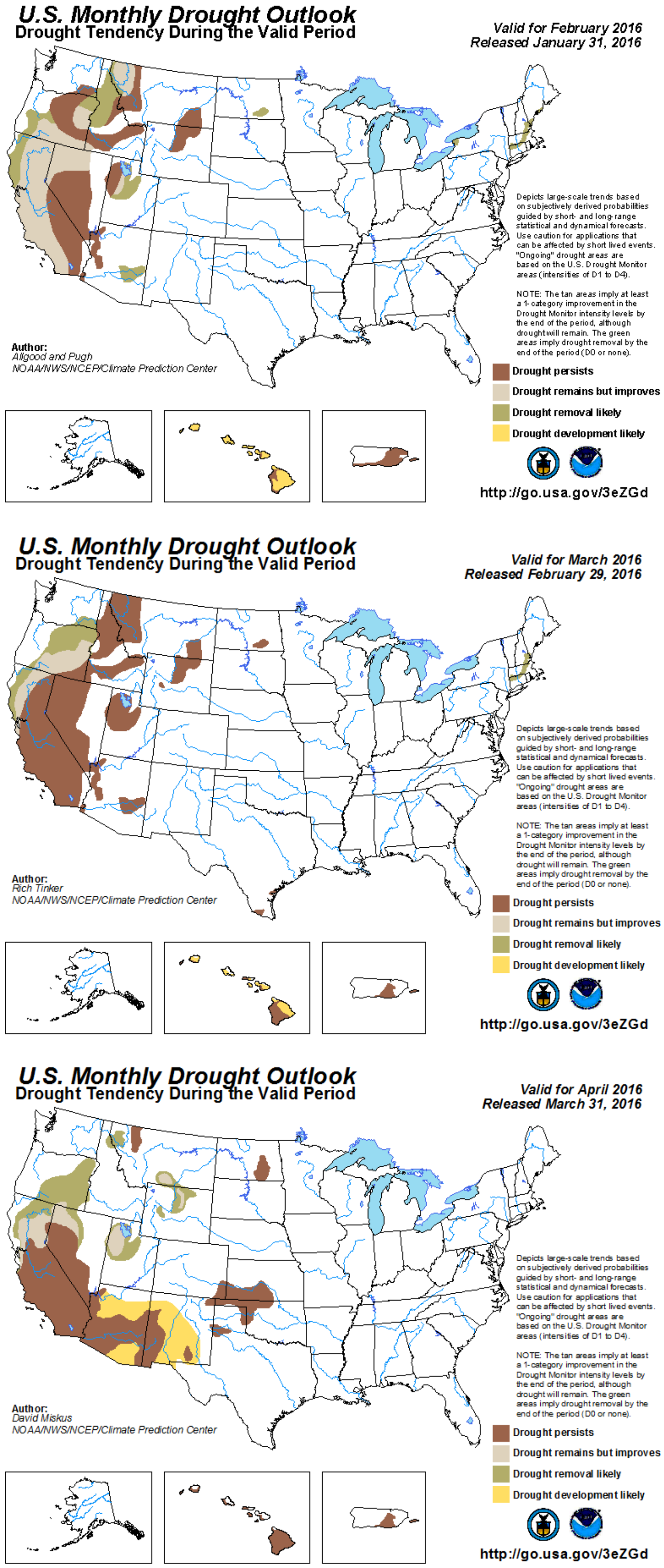

Figure B1. U.S. Monthly Drought Outlook: February, March, and April 2016

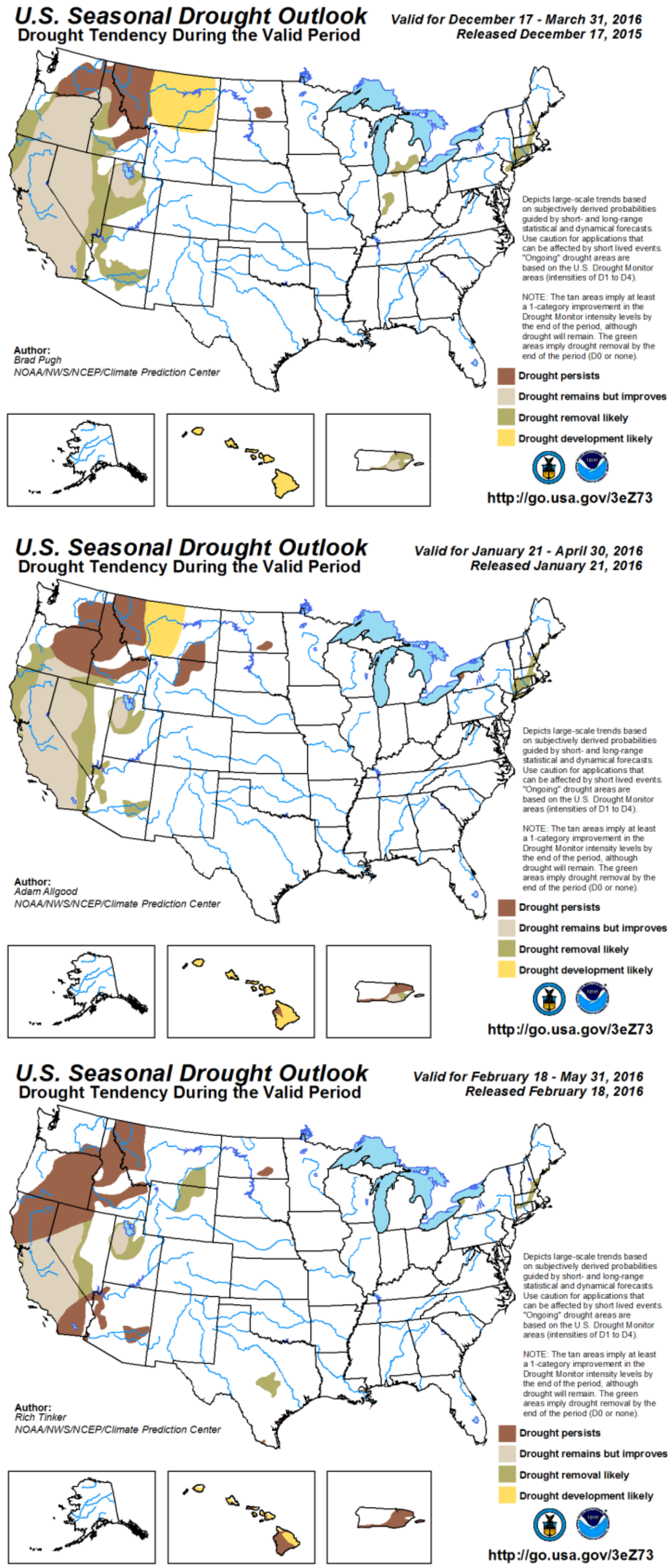

Figure B2. U.S. Seasonal Drought Outlook: Dec 2015-Mar 2016, Jan-April, Feb-May 2016

We are implicitly setting these coefficients to zero, though there may have been some positive effect. That is, adoption may have been higher during the 2016 season (or subsequent seasons) had NOAA or other forecast-producing groups predicted major widespread drought, *and* if these forecasts were to enter U.S. farmers' decision making.

However, evidence on the extent to which farmers use seasonal or sub-seasonal forecasts for planting-time decisions, especially choice of particular varieties, conditional on broader crop choice, needs further exploration. Patt et al. (2005) found that Zimbabwean farmers who used seasonal rainfall forecasts for the 2003-04 season had marginally significantly higher relative harvests than those who did not use forecasts. A year earlier, in 2002, these farmers made use of the forecasts by planting a greater proportion of their fields earlier, and with short-season varieties, though no significant effects on relative harvests were found between forecast users and non-users in this year. In the United States, relatively well-educated organic farmers in Georgia use and act on climate information, but climate forecasting remains poorly understood (Furman et al., 2011).

The 2016 ARMS questionnaire did not ask U.S. farmers if they used weather or climate information to inform their choice of variety on their corn fields. However, 57% of farmers in our sample indicated they used weather data to "assist in determining either the need or when to make pesticide applications" (USDA-ERS, 2016). Use of weather data for chemical applications, however, is expected to differ significantly from seasonal forecast use for varietal decisions. Very near-term wind, temperature, and rainfall conditions are main determinants of farmers' application timing due to concerns about pesticide drift and volatilization, moisture necessary for activation of chemical compounds, or pesticide leaching or runoff (Sexton et al., 2007). We conclude that more information is needed to assess, on a national scale, the full extent of U.S. farmers' forecast use.

Appendix C Spatial Variation in Relative Drought-Tolerant Corn Prices

Although prices of certain agricultural inputs and outputs, like pesticides and expected crop prices, have been assumed in past studies to be constant within a given year (e.g., Perry et al., 2016), recent evidence from roughly 12,000 corn seed invoices from U.S. farmers suggests there may be broad spatial variation in drought-tolerant corn variety prices (Farmers Business Network, 2018a). Based on a listing of 11,300 corn seed prices for 2,300 U.S. corn varieties, the authors find evidence of "zone" pricing. U.S. farmers within the same zone pay identical or nearly identical prices for the same traited variety, while farmers outside of these zones pay different prices for the same variety. As one example, they find evidence for 14 distinct pricing zones for an aggregate of Monsanto-branded seeds in their sample across 14 (mainly Midwestern) states.

To assess the potential effects of omitted seed pricing of drought-tolerant varieties, we re-do the analyses contained in tables 2 and 3 using publicly-available information on the prices of these DT varieties (Farmers Business Network, 2018a). In particular, we are able to construct the relative price for a particular type of drought tolerance, Monsanto Genuity DroughtGard®. State-level pricing data are available for VT Double PRO® seeds, an insect-resistant variety with two modes of action against above-ground corn pests, as well as VT Double PRO® with DroughtGard® drought tolerance. By constructing a price ratio for these two varieties, we are able to isolate a drought tolerance premium. Median list prices and actual (equilibrium) prices are available for both Monsanto varieties. Median seed prices are preferable to average seed prices since a range of discount types—bundling, early payment, loyalty, new customer, and volume—can produce outlying price points that would skew the average (Farmers Business Network, 2018b).

Averaged across states, the median list price ratio is 1.024 and the actual price ratio is 1.017. In level terms, the median list price of the DT seeds is $7.50 per bag more expensive, on average, than the identically-traited but non-DT seeds. The per-bag premium based on actual prices is $4.00. These are somewhat lower than the national estimate of a $10 per-bag DT premium (McFadden et al., 2019).

There are three main caveats with this pricing data used for this robustness analysis. First, Monsanto was the only seed firm offering a genetically-engineered (GE) DT trait in 2016, unlike DuPont Pioneer and Syngenta that offered corn seeds with conventionally-bred drought tolerance. Owing to differences in functionality, relative prices for GE drought tolerance could differ from non-GE drought tolerance (McFadden et al., 2019). Second, the pricing data are only available for six states: Illinois, Iowa, Kansas, Minnesota, Nebraska, and South Dakota. Collectively, these states accounted for 62.7% of 2016 U.S. corn acreage (USDA-ERS, 2016) but 69.5% of 2016 DT corn acreage (McFadden et al, 2019). The reduced sample size ensures more focus on relevant corn-producing states, as well as some states with significant DT acreage (e.g., Kansas and Nebraska), but results in far fewer clusters for standard error calculations. More importantly, the lack of finer-level variation in the price ratio rules out our ability to re-estimate the Spatial First Difference (SFD) results in table 5. Third, even within a particular set of GE or non-GE varieties, the DT premium may vary across other traits. In other words, the "base" set of traits might matter if it is costlier for companies to add the drought tolerance trait to varieties with certain combinations of traits relative to other combinations. This latter caveat is unlikely to be of much significance in our sample given the economics of research and development (R&D) in global seed markets (Heisey and Day Rubenstein, 2015). There are substantial fixed costs for trait innovations arising from significant R&D investments, lower incremental costs for combining seeds with two or more traits, and minimal marginal costs for actual seed production.

We find that median DT corn seed premiums are not statistically for both the mean-variance-motivated model and the Prospect-Theory-motivated models (tables C1 and C2).[2] This reduces some concern that the main set of estimates reported in the paper suffer from bias due to an omitted DT premium variable.[3]

Due to the smaller sample, the coefficients are estimated less precisely than those reported in tables 2 and 3, but they are similar in sign and magnitude. Relative to table 2, the impact of 30-year average temperatures is at least 2.75 times larger, and the irrigation-clay interaction term is roughly 27%-30% larger. The effect of highly erodible soils roughly doubles. There are similar changes in magnitude for these three variables in table C2, though these estimates exhibit slightly more differences from those of table 3.

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[2] For conciseness, we produce results only for specifications (1a) for the linear probability model from tables 2 and 3. The results are very similar for the other specifications in tables 2 and 3, as well as for the marginal effects from the probit model. The full set of robustness checks are available upon request.
[3] The 2016 ARMS questionnaire inquired about farmers' seed costs, but there is significant item non-response. However, it is possible to estimate shadow prices for certain GE traits, including drought tolerance, though the resulting coefficients are noisy in some cases. We leave for future research a full analysis of hedonic trait pricing.

Table C1: Mean-Variance-based Model Re-estimated with Median Drought-Tolerant Seed Premiums

	LPM (marginal effects)		
	Drought risk & climate		
	(1a)	(2a)	(3a)
Drought risk	0.065	0.075	0.070
	(0.132)	(0.135)	(0.129)
30-year temp mean	0.063***	0.068***	0.060**
	(0.020)	(0.022)	(0.026)
30-year temp std dev	0.345	0.470	0.368
	(0.643)	(0.649)	(0.622)
30-year precip mean	-0.091	-0.123	-0.088
	(0.149)	(0.156)	(0.149)
30-year precip std dev	0.102	0.136	0.103
	(0.161)	(0.168)	(0.161)
Irrigation	-0.101	-0.125	-0.102
	(0.089)	(0.096)	(0.089)
Irrigation x non-irrigated corn share	0.116	0.146	0.119
	(0.156)	(0.164)	(0.153)
Clay	-0.019	-0.023	-0.019
	(0.050)	(0.051)	(0.050)
Irrigation x clay	0.838***	0.854***	0.838***
	(0.255)	(0.249)	(0.255)
Irrigation x non-irrigated corn share x clay	-1.042	-1.067	-1.044
	(0.664)	(0.658)	(0.661)
Highly erodible	0.151***	0.148**	0.151***
	(0.056)	(0.056)	(0.056)
Corn-soy soil index mean	0.012	0.007	0.012
	(0.020)	(0.020)	(0.020)
Corn-soy soil index std dev	0.012	0.013	0.012
	(0.047)	(0.048)	(0.047)
February 2016 basis	-0.295	-0.242	-0.309
	(0.319)	(0.328)	(0.340)
Median DT corn premium, list		0.870	
		(1.058)	
Median DT corn premium, actual			0.446
			(2.672)
Constant	-1.792	-2.895	-2.251
	(1.374)	(2.032)	(2.687)
Observations	764	764	764
Correctly classified (%)	76	76	76
F-statistic	2.81***	2.58**	2.70***
R-squared	0.07	0.07	0.07

Note: Estimates are expanded to the population of U.S. corn fields in 2016 using a base expansion factor calibrated by USDA-National Agricultural Statistics Service. Standard errors in parentheses are clustered at the crop reporting district (CRD) level. There are 50 clusters. Exactly two of the predicted probabilities across the three models were less than zero and none exceeded one. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.

Table C2. Prospect-Theory-Based Model Re-Estimated with Median Drought-Tolerant Seed Premiums

	LPM (marginal effects)		
	Drought shocks & climate		
	(1a)	(2a)	(3a)
Severe-or-greater drought duration	0.003	0.002	0.003
	(0.006)	(0.005)	(0.006)
Maximum drought intensity	-0.018	-0.012	-0.019
	(0.036)	(0.039)	(0.035)
30-year temp mean	0.063***	0.067***	0.060**
	(0.021)	(0.023)	(0.027)
30-year temp std dev	0.356	0.455	0.382
	(0.655)	(0.658)	(0.621)
30-year precip mean	-0.119	-0.144	-0.117
	(0.134)	(0.147)	(0.135)
30-year precip std dev	0.127	0.159	0.129
	(0.162)	(0.176)	(0.160)
Irrigation	-0.083	-0.102	-0.083
	(0.114)	(0.121)	(0.114)
Irrigation x non-irrigated corn share	0.085	0.113	0.087
	(0.152)	(0.159)	(0.150)
Clay	-0.025	-0.027	-0.025
	(0.048)	(0.049)	(0.048)
Irrigation x clay	0.858***	0.869***	0.859***
	(0.259)	(0.252)	(0.259)
Irrigation x non-irrigated corn share x clay	-1.053	-1.076	-1.056
	(0.668)	(0.655)	(0.664)
Highly erodible	0.153***	0.150***	0.153***
	(0.055)	(0.055)	(0.055)
Corn-soy soil index mean	0.011	0.007	0.011
	(0.020)	(0.020)	(0.020)
Corn-soy soil index std dev	0.009	0.009	0.009
	(0.051)	(0.051)	(0.051)
February 2016 basis	-0.293	-0.269	-0.309
	(0.319)	(0.317)	(0.345)
Median DT corn premium, list		0.698	
		(1.125)	
Median DT corn premium, actual			0.511
			(2.705)
Constant	-1.537	-2.425	-2.048
	(1.136)	(1.881)	(2.579)
Observations	764	764	764
Correctly classified (%)	76	76	76
F-statistic	2.69***	2.49**	2.59***
R-squared	0.07	0.07	0.07

Note: Estimates are expanded to the population of U.S. corn fields in 2016 using a base expansion factor calibrated by USDA-National Agricultural Statistics Service. Standard errors in parentheses are clustered at the crop reporting district (CRD) level. There are 50 clusters. Exactly two of the predicted probabilities across the three models were less than zero and none exceeded one. Significance is denoted as ***p<0.01, **p<0.05, and *p<0.10.

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