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Measuring the Adaptive Response to Drought

Kyle Eagar

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Measuring the Adaptive Response to Drought

by

Kyle Eagar

A research paper submitted in the partial fulfillment
of the requirements for the degree

of

MASTER OF SCIENCE

in

Economics and Statistics

Approved:

Eric Edwards
Major Professor

Man-Keun Kim
Committee Member

Ryan Bosworth
Committee Member

UTAH STATE UNIVERSITY
Logan, Utah

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ABSTRACT

Measuring the Adaptive Response to Drought

by

Kyle Eagar, Master of Science

Utah State University, 2017

Major Professor: Dr. Eric Edwards

Department: Applied Economics

Scientific evidence suggests that future climate change has the potential to bring about an increase in both the frequency and duration of drought in some regions of the world (United Nations, 2012). Economists have theorized that at least some of the adverse effects of these droughts will be mitigated through various adaptive responses by agricultural producers. The effectiveness of any adaptive response to climate change will depend on how quickly producers can recognize a change in climatic patterns and respond accordingly. The following paper investigates the relationship between a specific climate signal (prolonged drought) and the land use decision of a farmer. To accomplish this, we track changes in land use for roughly 50,000 farmers for 5 consecutive years in western Kansas. Using a two-way fixed effect model, we find a statistically significant negative association between drought and the decision to plant corn, a relatively more water intensive crop. However, the magnitude and statistical significance of these findings are quite sensitive to model specification. In addition, although statistically significant, the magnitude of this relationship appears to be small, suggesting that the pace of climate change adaptation, with respect to drought and crop choice, may be quite gradual.

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Introduction

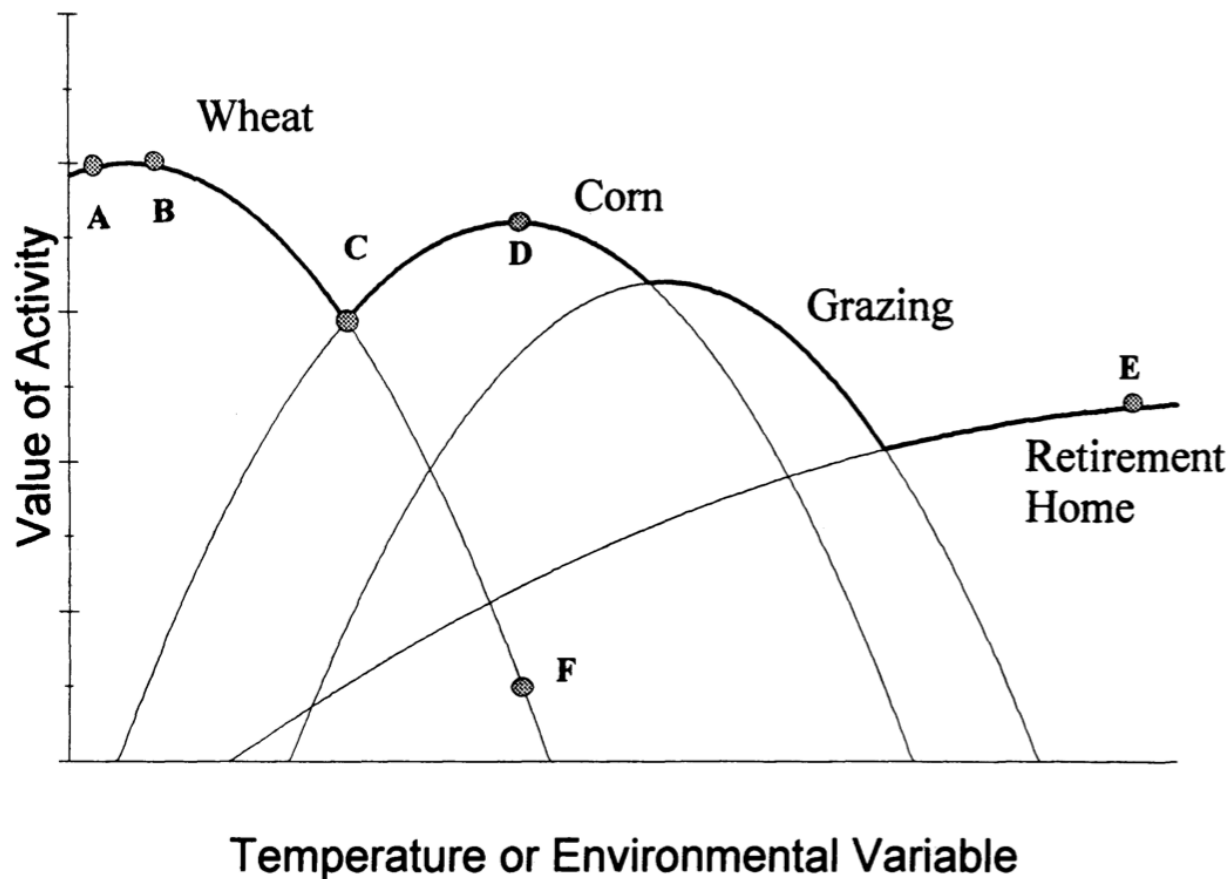
Many climate forecasts predict an increase in the frequency of short-term droughts (those lasting 4-6 months), and long term droughts (those lasting more than a year) (Sheffield & Wood, 2008). Although climate change may be associated with an increase in average yearly precipitation globally, it will likely also be accompanied by an increase in the year to year variability of rainfall (Environmental Protection Agency, 2016) (Richmond, Yohe, & Melillo, 2014). Higher variability in precipitation could mean more extreme weather events, such as floods and droughts. These changes are of concern to the agricultural sector given that drought is one of the most “serious production shocks a farm can experience” (United States Department of Agriculture, 2016). For instance, the USDA estimates that “over the past decade, total drought-related crop insurance indemnities and disaster relief payments averaged \$4 billion per year, up from less than \$1.3 billion per year in the 1980s” (United States Department of Agriculture, 2016). In addition, the United Nations refers to drought as the “world’s costliest natural disaster” (United Nations, 2014).

Although it is natural to suppose that an increase in mean rainfall will be a more favorable condition for agriculture, we should also be attentive to the ways that increased variability in year to year precipitation could be harmful. A standard microeconomic assumption is that there is diminishing marginal product of crop yields with respect to water input. A consequence of these diminishing returns is that a decrease in water availability reduces agricultural revenue in absolute terms more than an equivalent increase in water input raises revenue. Under the assumptions of production function concavity, an increase in variability of water access reduces expected revenue, *ceteris paribus* (Gemma & Tsur, 2007). The assumption of diminishing marginal product with respect to water appears to be empirically validated for some crops (Rogers & Jonathan, 2015) (Brumbelow & Georgakakos, 2007) (Trout & Bausch, 2012). The significance of this is substantial

given that, as mentioned before, climate change may be associated with an increase in both the mean and standard deviation of seasonal precipitation.

Much of the well-cited research on climate change adaptation in agriculture has been focused on temperature rather than precipitation as the variable of analysis (Fisher & Hanemann, 2006) (Adams, 1989) (Mendelsohn, Nordhaus, & Shaw, 1994) (Deschene & Greenstone, 2007). Although the focus of this paper is drought, the theoretical foundations are similar to those concentrating on temperature, so they will be discussed briefly.

Climate change adaptation research in agriculture is guided by the acknowledgment that a farmer's profit maximizing crop choice largely depends on his or her available inputs. The implication of this is that as certain input constraints change due to climate change so may the optimal crop choice. An influential diagram that effectively depicts this concept was given in *The Impact of Global Warming on Agriculture: A Ricardian Analysis* see **Figure 1** (Mendelsohn, Nordhaus, & Shaw, 1994). The y-axis in this diagram gives the value of various economic activities and the x-axis represents temperature or another environmental variable. The four parabolas represent the relationship between the environmental variable and the corresponding economic benefit of a particular activity. In the hypothetical scenario represented in the graph, when the environmental variable is low, the optimal production decision is to plant wheat (Point B). As the environmental variable increases, wheat production decreases in value while corn production increases. If a farmer cannot switch out of wheat as the climate changes, then he or she will receive the lower value F. However, if a farmer chooses to adapt to this change by switching crops, he or she will receive value D as opposed to F.



Note: Taken from *The Impact of Global Warming on Agriculture: A Ricardian Analysis* pg 3 (Mendelsohn, Nordhaus, & Shaw, 1994)

FIGURE 1. "Bias in Production-Function Studies"

Models intended to estimate the social costs of climate change that do not incorporate the adaptive capabilities of agricultural producers have been criticized as "dumb farmer models" by some economists (Mendelsohn, Nordhaus, & Shaw, 1994). The criticism being that they assume that an agricultural producer will continue to plant the same crop even when their input endowment has changed drastically due to climate change. Empirical estimates regarding the future social costs of climate change that don't incorporate the adaptive capabilities of economic agents will tend to produce an upward bias (Adams, 1989).

When it comes to drought, there is evidence that some farmers respond to drought by switching crops. For instance, research suggests that a Kenyan farmer's "crop diversification choices are driven by persistent climatic shocks" (Martina, Di Falco, Smale, & Swanson, 2014)

However, other qualitative research involving interviews with Mexican farmers suggests that “adaptation will be far more complex than simply adjustments in crop type” (Eakin, 2001).

Historically, it does appear that changes in water availability over the past century has resulted in sizable changes in land use in the United States. For instance, after the Ogallala aquifer first became accessible to farmers during the 1950’s and 1960’s, a change to more water intensive forms of land use in western Kansas was observed (Hornbeck & Keskin, 2011). This is consistent with the view that farmers modify their production decisions in response to changes in their input constraints. In the future, as input constraints change due to climate change, we might expect more climate appropriate forms of land use. However, just how large these adaptation capabilities will be in the future is still a challenging empirical question. The following statistical analysis contributes to the climate adaption literature by attempting to measure the relationship between drought and crop selection.

Theory and Methodology

Do farmers respond to drought by planting less water intensive crops? If so, is this due to changes in their beliefs regarding future weather patterns? In this section, a simple theoretical model is introduced to explain why an agricultural producer may switch crops in response to changes in expected weather patterns.

Consider a hypothetical scenario where an agricultural producer has the option to plant one of two crops, either crop A or crop B. The revenue functions for crop A and crop B are graphed in **Figure 2**. Crop A generates more revenue for the farmer only under higher levels of rainfall. If the agricultural producer experiences abundant rainfall (denoted W), it is more profitable to plant crop A (revenue function represented by the red line). However, if he or she experiences low levels of rainfall (denoted D) it becomes preferable to plant crop B (revenue function represented by the blue line).

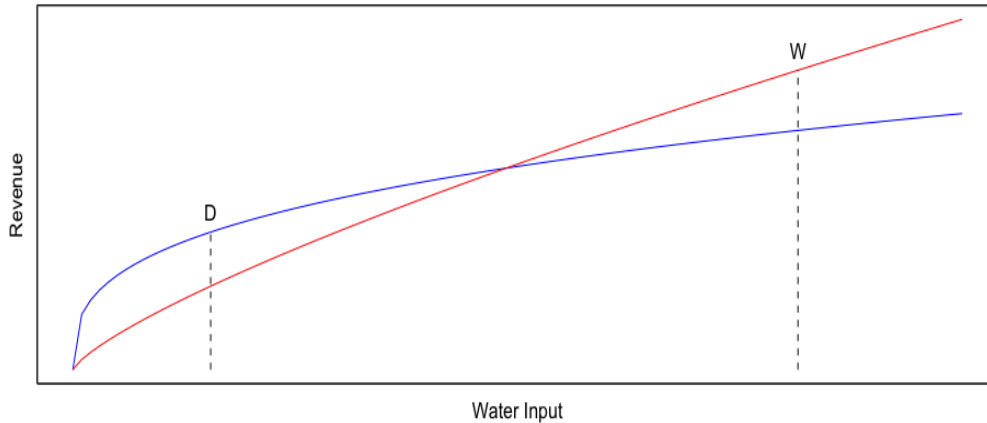


Figure 2 Revenue from Water Intensive Crop and Non Water Intensive Crop

If the farmers knew with certainty whether they would experience W or D in a particular season, they would simply plant the crop that maximizes revenue give their anticipated level of water input. However, seasonal precipitation is a random variable. We assume a profit maximizing farmer will choose the crop that maximizes expected revenue $E(R)$. Equations E.1 and E.2 are the expected revenue functions for planting crop A (water intensive crop) and crop B (non-water intensive crop).

$$\text{E.1 } E_A(R) = pf_A(W) + (1 - p)f_A(D)$$

$$\text{E.2 } E_B(R) = pf_B(W) + (1 - p)f_B(D)$$

p is the probability of W and $(1 - p)$ is the probability of D . f_A and f_B are the revenue functions that correspond to a farmer planting crop A or crop B, respectively. The farmer does not intrinsically know p but instead must develop a belief about p through years of observation. The farmer also doesn't necessarily know the functional forms of f_a and f_b , but again must acquire this knowledge through observation. After a farmer experiences D he updates his belief about $(1 - p)$, the probability of D . This in turn influences his or her perceptions of $E_a(R)$ and $E_b(R)$. Any change in the perception of p or $(1 - p)$ due to an observation of W or D may prompt a farmer to switch crops because their perceptions of $E_a(R)$ and $E_b(R)$ have changed.

To test this model, we examine the relationship between drought and the decision to plant a water intensive crop. Given that corn is the most well represented water intensive crop in western

Kansas it is a natural candidate for the dependent variable (Rogers & Jonathan, 2015). Even though there are other water intensive crops being planted in the region, their numbers are relatively small compared to total agricultural land (see **Appendix A**). For instance, cotton is a well-known water intensive crop, however, it only accounts for a small percentage of total crop land being used in western Kansas. The econometric model intended to estimate this relationship is given in equation E.3 below.

$$E.3 \quad Y_{it} = \beta_0 + \sum_{l=0}^L D_{i,(t-l)} x_i + \sum_{t=1}^T \beta_t x_i + \sum_{i=1}^I \beta_i x_i + \epsilon_{it}$$

Y_{it} is a binary variable equaling 1 if parcel i chooses to plant corn in time period t .

$\sum_{l=0}^L D_{i,(t-l)} x_i$ is a sequence of lagged binary variables that equal 1 if parcel i experienced drought in year $t - l$, where L is the number of lagged variables. $\sum_{t=1}^T \beta_t x_t$ are year fixed effects, intended to control for un-observed variation across time that is influencing all parcels in the data set simultaneously. Parcel fixed effects, $\sum_{i=1}^I \beta_i x_i$, control for un-observed variations across parcels that is constant over time. And finally, β_0 and ϵ_{it} represent the intercept coefficient and the error term respectively. A linear probability model is employed due to its interpretability and less stringent assumptions about the distribution of the error term.

By including parcel-level fixed effects, we control for all omitted variables that are constant over time, yet different across entities. These may include soil quality, distance to the market, slope of the land, local infrastructure, etc. Year fixed effects are able to control for all omitted variables that simultaneously impact every parcel in the dataset but are changing over time. Some of these variables include crop prices as well as certain input prices.

This two-way fixed effect model by itself cannot control for omitted variables that vary across parcels, while at the same time vary over time. Some of these potential confounding factors may include temperature, cloud cover, changes in access to surface or groundwater, as well as local policy responses to drought. There is always the possibility that these uncontrolled factors may be

correlated with the error term ϵ_{it} which in turn would bias the estimate $\sum_{l=0}^L D_{i,(t-l)}x_i$. The omitted variable that has the most potential to bias the results is changes in groundwater access due to drought. It has been empirically verified that farmers pump more ground water during times of drought (Peterson, Ding, & Roe, 2003). The implication of this is that it may be difficult to distinguish between a farmer switching out of corn due to changes in their perceptions regarding the probability of drought, and switching crops because of groundwater depletion.

It should also be noted that the Ogallala aquifer, which lies under much of this region, is essentially a nonrenewable resource, experiencing only a few inches of recharge every year. The implication of this is that aquifer depletion, due to increased pumping during times of drought, could influence planting decisions for years to come, given that pumping costs increase as water levels decline. To address this concern, in the following section regression results for those that don't have access to groundwater are compared to those that do.

Data for the dependent variable, the decision to plant corn, was taken from the National Agriculture Statistical Service (NASS, Cropscape-Crop Data, 2015). NASS provides yearly data on land use decisions for much of the United States. Because of this we are able to track changes in land use over the course of many years. The time of the year that this data was captured by means of satellite imagery is between June and August (NASS, CropScape and Cropland Data Layers, 2016). In the end, land use was tracked for approximately 50,000 parcels of land for a total of 5 years.

The treatment variable, drought $D_{i,(t-l)}$, was retrieved from the National Weather Service for the month of April, the pre-planting season for corn (NWS, 2015). The chosen index of drought is known as the Palmer Drought Index which is “standardized to local climate, so it can be applied to any part of the country to demonstrate relative drought or rainfall conditions.” (USGS 2016). This index “*is most effective in determining long term drought (a matter of several months) and is not as good with short-*

term forecasts (a matter of weeks)" (USGS 2016). The palmer index goes from -4 (severe drought) to 0 (no drought).

One natural question is whether or not there is enough variation in the independent variables across parcels in western Kansas to identify the effects of drought, given that year fixed effects are included in the model. To address this question, **Table 1** gives the percent of agricultural parcels that experienced drought for the years 2011-2015. During most years, the majority of agricultural parcels did not experience drought. To help visually demonstrate this **Appendix B** provides a drought map for the year 2011.

Table 1 Percent of Farmers Experiencing Drought by Year

Year	2011	2012	2013	2014	2015
% PDI < 0	19.13%	13.08%	31.14%	31.41%	29.08%

Another important issue pertains to the flexibility that farmers have in switching between various crops year to year. Changes in the percent of farmers planting corn is provided in **Table 2** for the years 2006 and 2015. The data suggests that changes in land use over time can be noticeable even within a relatively short time period.

Table 2 Percent of Farmers Planting Corn by Year

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
% Corn	11.4%	16.6%	14.9%	15.6%	19.2%	19.1%	16.6%	16.7%	16.1%	15.9%

Results

At this point we estimate equation E.3 using three groups; all farmers, only those that have groundwater, and those with no groundwater. The dependent variable, the decision to plant corn, is regressed on lagged dummy variables, indicating that a given parcel has experienced drought for that year. **Table 4** provides the results of this LPM combined with two-way fixed effects for the three groups.

Regression 1 includes only farmland that has at least some groundwater as of 2012. It appears that drought is negatively associated with the probability of planting corn. However, this relationship is identifiable only with considerable lag. Adding the statistically significant lags together gives use a long run propensity of -.0275. Again it is unclear if these results are due to aquifer depletion or if farmers have changed their expectations regarding the probability of drought.

Regression 2 includes only farmers that do not have groundwater under their land. It appears that although past drought influences the decision to plant corn, the long run propensity is smaller than for those that have groundwater. The long run propensity being -.012 for dry land farmers compared to -.0275 for those that have groundwater. This is consistent with the view that some of the change is due to groundwater depletion as opposed to adaptive expectations.

Regression 3 includes both dry and irrigated farm land. The results are similar to regression 1 with drought being negatively associated with corn production, but only with a considerable lag.

Table 3 Drought and the Decision to Plant Corn

Dependent Variable: $Y_{it} = 1$ if Farmer Planted Corn			
Regression #	Regression 1	Regression 2	Regression 3
Description	Parcels with Ground Water	Parcels with No Ground Water	Combined
Drought	-.0018 p=.66	.0019 p=.63	-.00011 p = .96
Drought Lag 1	.0061 p=.084 *	.0016 p=.66	0.00426 p = .12
Drought Lag 2	-.0003 p=.91	.0020 p=.59	-.00006 p = .98
Drought Lag 3	-.0101 p=.0061 **	-.0122 p = .0037 **	-.01082 p=.00026 ***
Drought Lag 4	-.0174 p=.00002 ***	-.0035 p = .425	-.0133 p = .00004 ***
\bar{R}^2	.43	.224	.42
N	130,820	58,923	189,752

* p < .1 ** p < .01 *** p < .001

Note: p values calculated using heteroskedastic robust standard error

Are these results economically significant? During the years 2011-2015, on average 24.75% of the 51,850 parcels in the data set had a palmer drought index less than 0 (see table 2). The long

run propensity for those with no groundwater (Regression 2) is our estimate of the adaptive response to drought. Applying this estimate to the average number of farmers that experienced drought for the years 2011-2015, we get an estimate of 156 farmers a year eventually switching out of corn due to drought. This represents about a third of a percentage point of the number of parcels in the data set. An estimate of the dollar amount saved due to adaption would require a knowledge of what crops these farmers switched to, as well as the expected revenue for these crops under future weather patterns.

The amount of time it takes for a farmer to respond to drought is highly pertinent information. Given that the regression results suggest a large delay between the time of drought and the time of adaptation we are curious to what barriers are preventing a quicker response. It could be that there are substantial costs involved in learning to plant and harvest a new crop. Specialized equipment might be necessary and considerable research may need to be performed before committing to a new crop rotation. These switching costs could explain why there is such a considerable lag between the realization of drought and a decrease in the probability of planting corn.

To see how sensitive the results are to changes in how the treatment variable is defined, three additional regressions are provided in **table 5**. In these models the independent variable is an integer signifying the number of years a parcel has experienced drought over the past 6 years. Farmers that have experienced more drought over the past 6 years should be less likely to plant corn if the adaptive response hypotheses is correct. We see from regression 2 (parcels with no groundwater), that there is no sign of statistical significance whatsoever. This alerts us to the sensitivity regarding how the treatment variable is defined. This should warrant more cautious interpretation of the results in both tables 4 and 5.

Table 4 Number of Droughts Over Past Six Years

Dependent Variable: $Y_{it} = 1$ if Farmer Planted Corn			
Regression #	Regression 1	Regression 2	Regression 3
Description	Parcels with Ground Water	Parcels with No Ground Water	Combined
# of Drought Years over the past Six Years	-.0033 p=.04 *	-0.0018 p=.63	-.002 p = .02 *
\bar{R}^2	.43	.59	.42
N	130,824	58,927	189,756

* p < .1 ** p < .01 *** p < .001

Note: p values calculated using heteroskedastic robust standard error

Conclusion

The hypotheses that farms develop adaptive expectations regarding the probability of drought is not strongly supported by the results of this study. This doesn't necessarily mean that farmers will not adapt to future drought by switching to less water intensive crops, but that this transition may occur in a much longer time frame than this study was able to provide. Although statistically significant results were found, the practical relevance of these effects is questionable. This is especially true considering how sensitive the results are to the specification of the treatment variable (compare table 4 with table 5).

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APPENDICES

Appendix A

The table below provides the frequency and percent of times that farmers planted a given crop for the years 2006-2015.

Crop	N	Percent
Alfalfa	14786	3.04924%
Barley	17	0.00351%
Canola	39	0.00804%
Corn	78307	16.14884%
Cotton	274	0.05651%
Db1 Crop Barley/Corn	1	0.00021%
Db1 Crop Barley/Sorghum	1	0.00021%
Db1 Crop Oats/Corn	1	0.00021%
Db1 Crop Soybeans/Oats	1	0.00021%
Db1 Crop WinWht/Corn	1	0.00021%
Db1 Crop WinWht/Sorghum	1	0.00021%
Db1 Crop WinWht/Soybeans	9620	1.98388%
Dry Beans	2	0.00041%
Durum Wheat	1	0.00021%
Fallow/Idle Cropland	64262	13.25241%
Millet	26	0.00536%
Oats	135	0.02784%
Other Crops	1	0.00021%
Other Hay/Non Alfalfa	420	0.08661%
Other Small Grains	37	0.00763%
Peas	49	0.01011%
Potatoes	54	0.01114%
Rye	1547	0.31903%
Safflower	1	0.00021%
Sorghum	48014	9.90167%
Soybeans	33950	7.00133%
Spring Wheat	5	0.00103%
Sunflower	326	0.06723%
Sweet Corn	1	0.00021%
Switchgrass	4	0.00082%
Triticale	1	0.00021%
Winter Wheat	233023	48.05509%

Appendix B

The drought map below is intended to show the variation of drought coverage for the year 2011. Darker shades of red indicate more severe drought. Dark grey indicates the Ogallala Aquifer.

