The Impact of Weather Extremes on Agricultural Production Methods: Does drought increase adoption of conservation tillage practices?

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Abstract

The adoption of conservation tillage practices such as ridge till, mulch till, or no-till has been shown to reduce soil erosion. An additional benefit of these conservation practices is that they also increase soil moisture. Therefore, these practices appear to be a method that agricultural producers can use to reduce their risk associated with abnormally dry or wet conditions (i.e., drought or flood). Given the large amount of money spent by the USDA on crop insurance indemnity and ad-hoc disaster relief payments, practices that reduce the risk of drought to the farmer should be strongly encouraged. Using SUR estimation with random effects, the paper uses panel data to measure the impact of extreme weather events on the adoption of conservation tillage. Panel data allows the identification of differences in adoption rates as a function of the severity of the drought or flood event. The adoption of no-till, alternative conservation tillage, and reduced till are estimated relative to conventional tillage. Both extremely dry and extremely wet conditions are found to increase the adoption of conservation tillage; while extremely wet conditions increase the adoption of both no-till and other conservation tillage practices.

Introduction

A large amount of government spending in the United States is devoted to programs that help farmers manage risk. Programs such as federal crop insurance subsidize farmer's premiums for risk-reducing insurance policies, with the subsidy varying by type of policy and level of coverage (Glauber 2004). In addition to crop insurance programs, ad-hoc disaster payments are frequently used to reimburse farmers after natural disasters occur. Drought is the most cited reason for ad-hoc disaster payments, although floods are also a common cause (Garrett et al. 2004). For example, P.L. 108-7 of 2003 provided $3.1 billion to crop and livestock producers in counties affected by drought during the 2001 and 2002 seasons, while P.L. 103-75 of 1993 provided $2.5 billion to Midwest producers impacted by flood (Chite 2006). These ad-hoc disaster payments have continued in recent years, despite changes to the federal crop insurance program designed to increase the level of enrollment and reduce the need for disaster payments (Glauber and Collins 2002).

It is well-known that crop insurance programs are fraught with problems, including adverse-selection and moral hazard, although increased participation rates have reduced this. There has been a significant amount of economic literature that provides recommendations on how the suite of federal crop insurance and disaster payment programs can be improved (see Glauber 2004 for an excellent overview of the history of crop insurance programs and related literature). It is expected that without reform, these costs will continue to increase due to climate change and increased occurrences of extreme weather events such as floods and droughts (Frederick and Schwarz 2000). However, the adoption of risk-reducing agricultural practices is one method that farmers can use to protect themselves against such events.

In this paper, we estimate the impact of short-term precipitation shocks (i.e., drought and flood) on the adoption of risk-reducing production methods. Previous studies have found that drought significantly increases the adoption of water-conserving irrigation systems (Zilberman et al. 1995; Carey and Zilberman 2002); however the impact of such extreme weather events on tillage practices has not been studied. No-till agriculture (i.e., zero tillage) is a way of growing crops from year to year without plowing the soil, a practice that results in increased levels of crop residues in the field. Due to the fact that no-till conserves soil moisture, its adoption is one method that agricultural producers can use to reduce their risk associated with drought. According to the Conservation Tillage Information Center, the national percentage of no-till farmland increased 38 percent from 1998 to 2006, while the drought-impacted states of Nebraska, South Dakota, and Kansas saw an increase of 67 percent. Other factors affecting the adoption rates include labor and fuel costs, as no-till reduces the use of these inputs; and the development of the Environmental Quality Incentives Program (EQIP). Enacted in 1996 and expanded in 2002, EQIP provides financial incentives and technical assistance to farmers who are willing to adopt conservation tillage.

Previous studies on the adoption of conservation tillage often employed cross-sectional data to analyze the adoption decision in response to site-specific information (Soule et al.

2000; Kurkalova et al. 2006). Some key factors identified include land characteristics (e.g., land slope, soil texture, and soil productivity), farmer demographics (e.g., age, education level, and farming experience), and land tenure. One limitation of using cross-sectional data is that it is impossible to identify the effects of those variables which change over time but present little cross-sectional variation for a given time period, such as prices, weather and policy variables. Although previous studies of adoption include long-term average climate information as explanatory variables, they have failed to identify the impact short-term climate events. We expect that farmers are more sensitive to recent weather extremes than to long-term climate trends. To test this, we use panel data of pooled cross-sectional and time-series information in the study.

We estimate the adoption of three categories of tillage systems relative to conventional tillage: no-till, other conservation tillage, and reduced till. Our results show that farmers increase their adoption of conservation tillage practices in both abnormally dry and abnormally wet conditions, and that abnormally wet conditions increase the adoption of no-till systems. We also find evidence that the Environmental Quality Incentives Program (EQIP) has been successful in promoting the adoption of no-till, but has not had a similar effect on other conservation tillage.

Model Development

The adoption decision of alternative tillage practices is modeled as an optimal land allocation problem. An individual operator chooses the share of acreage allocated to each tillage system based on the site characteristics and inter-temporal factors. The maximization problem can be written as:

$$\text{(1)} \qquad \begin{aligned} &\Pi = \underset{s^m}{Max}(s^m \pi^m) \\ &s.t. \quad \sum s^m = 1 \end{aligned}$$

where s^m is the share of land planted with *m*-th tillage method. Previous studies on the choice of tillage systems often employed a multinomial logit adoption model using field level data (Soule et al. 2000; Wu and Babcock 1998; Kurkalova et al. 2006). However, because time-series information is not available at the field-level, county-level data are the most disaggregate available. Therefore, the county average values of land shares, site attributes and other economic variables are used in this study. Solving for the problem in (1), the share of tillage system *m* in county *i* at time *t* can be specified as:

$$\text{(2)} \qquad s_{it}^m = D^m(X_{it})$$

where X_{it} is a vector of explanatory variables including all site specific variables and/or time-varying variables which affect the adoption decision of alternative tillage systems.

Following previous studies on cropland allocation using county-level data (Lichtenberg 1989; Wu and Segerson 1995), the share equation, D^m is specified with the logistic functional form. Thus, s_{it}^m is written as:

(3) $$s_{it}^{m} = \frac{e^{X_{it}\beta^{m}}}{\sum_{m=0}^{M} e^{X_{it}\beta^{m}}}$$

where, M+1 alternative tillage systems are indexed by m=0, 1, … M. Choosing one tillage practice as the base category and normalizing its coefficients to zero, we have:

(4) $$\log(s_{it}^{m} / s_{it}^{0}) = X_{it}\beta^{m} + u_{it}^{m}$$

where β^{m} is the vector of coefficients to be estimated, and u_{it}^{m} is the vector of error component.

The vector of explanatory variables, X_{it} includes three types of variables: 1) cross-sectional and time-invariant variables, such as land characteristics, land tenure and farmer demographics; 2) time-series variables, which present little cross-sectional variation, such as prices and policy instruments; 3) cross-sectional and time-series data, such cropping patterns and weather extremes.

Data and Variables

In this study, we estimate the empirical model by using county-level data from three northern High Plains states (Kansas, Nebraska and South Dakota), and three eastern Corn Belt states (Illinois, Iowa and Missouri). In each of these states, there are significant acres planted with no-till or other conservation tillage methods, and the adoption rate is still increasing. The variables selected for analysis and their definitions are summarized in Table 1. Detailed descriptions of variables and data sources are presented as follows.

Dependent Variables

Tillage systems: Data on crop acreage of alternative tillage systems from 1990 to 2004 are obtained from the Crop Residue Management (CRM) Survey, conducted by the Conservation Technology Information Center (CTIC). By the most commonly used definition, conservation tillage is referred to any tillage system that leaves at least 30 percent residue cover on the soil surface after planting. The CRM survey collected information on three different conservation tillage systems (no-till, ridge-till, and mulch-till), reduced till (15-30 percent residue), and conventional till (more than 30 percent residue). Because the acreage of ridge-till is small in most counties of our study region, we aggregate ridge-till and mulch-till into one category called alternative conservation till. Thus, four categories of tillage systems are analyzed in the empirical model. We choose the conventional till as the base category; therefore, three share equations are estimated after normalization.

Explanatory Variables

Cross-sectional and Time-invariant Variables

Highly erodible land (HEL): Soil with an erodible index greater than 8 is defined as highly erodible land. Since reducing soil erosion is a major benefit associate with conservation till, operators farming on highly erodible land are more likely to adopt conservation till. And also, certain government programs require the participants to use conservation practices on highly erodible land to receive commodity payments and other program benefits. The data is obtained from USDA/NRCS SSURGO Soils Database, and National Agricultural Statistics Service Land Cover Satellite Image (2003).

Land slope: According to the study by Wu and Babcock, adoption rates of conservation tillage increase on highly-sloped land, due to greater benefits of soil-loss reduction. The slope gradients of each soil map unit are obtained from USDA/NRCS SSURGO Soils Database, and the county average of land slope is the weighted average of slope gradients of all soil map units within a county.

Land tenure: As it may take several years for conservation tillage to generate benefits, with respect to improved soil condition and crop response, we hypothesize that cash-renters are less likely to adopt conservation tillage than share-renters and owner-renters. The percentage of cropland operated by cash-renters is included into the explanatory function, and the data is from USDA/NASS.

Time-series variables

Fuel prices: The increasing fuel prices in recent years could be a major driving force in the adoption of no-till, as no-till reduces the machinery-related costs and fuel consumption. Fuel prices are obtained from DOE/EIA.[1]

Policy instruments: The 2002 Farm Bill included a shift in conservation programs. While previous farm bills had emphasized land retirement programs, the 2002 Farm Bill increased funding for the use of conservation practices on working land. The Environmental Quality Incentives Program (EQIP), enacted in 1996 and expanded in 2002, provides financial incentives and technical assistance to farmers who are willing to adopt conservation tillage. The effect of the EQIP assistance program is estimated by incorporating two dummy variables as indicators of the two different Farm Bills and funding levels for the EQIP program during the period of consideration (1997-2001 and 2002-2004).

Cross-sectional and Time-series Variables

Corn and soybean: The data suggest that conservation till is more frequently adopted with the production of corn and soybean. It is perhaps because corn has the relative slow rate at which ground cover is established in springtime. Since corn-soybean rotation is widely adopted in our study region, we incorporate the percentage of corn and soybean land into the explanatory function.

Irrigated land: Conservation tillage occurs more frequently on dryland than irrigated

[1] This variable is not included into the preliminary estimation as we do not have state-level data for the year 2004.

land, “perhaps because crop residue interferes with irrigation operations” (Wu and Babcock). In addition, irrigation availability allows farmers to be less concerned about soil moisture conditions. Therefore, the percentage of irrigated cropland in each county and at each year is incorporated into the empirical model, and the data is from USDA/NASS.

Farm size: As no-till requires initial investment in special equipment, large farms are more likely to adopt no-till than small farms. The number of farms in each county is used to indicate the average farm size in the county; a small number of farms means larger farm size. The data of farms number is obtained from USDA/NASS.

Conservation Reserve Program: Farmers with highly erodible land can either choose to enroll their land to CRP, or adopt conservation tillage to reduce soil erosion. Therefore, we hypothesize that CRP enrollment rate has negative effect on the adoption rate of conservation tillage. The data of acreage enrolled to CRP is obtained from USDA/FSA.

Weather extremes: Although previous studies often include the long-term average climate information into the explanatory function, they have failed to identify its significance in the adoption decision of tillage method. We hypothesize that farmers are more sensitive to the recent weather extremes than to long-term climate trends. The variables of weather extremes are constructed using Palmer Drought Severity Index (PDSI). This index provides measurements of moisture conditions that are standardized so that comparisons can be made between locations and across time periods (Palmer 1965). The Palmer Index usually varies between -4.0 and 4.0, with negative number indicating abnormally dry and positive number indicating abnormally wet. Palmer classifications are listed in Table 2.

Due to the fact that crop residue cover traps soil moisture, conservation till is one method that producers can use to reduce their risk associated with drought; therefore, more adoption of conservation till might occur after the multiple-year drought. On the other hand, rain is the largest cause of soil erosion. Heavy raindrops, sheet wash and the flow of water over the soil cause destructive damages. An effective method to fight this kind of erosion is to keep the soil covered, thus conservation till is preferred as it leaves more residue in the field. We hypothesize that both abnormally dry and wet weather conditions will increase the adoption of no-till and other conservation till. In the empirical model, the January PDSI is used to measure the moisture condition of the previous year. If PDSI<-2, the year is defined as dry year; and if PDSI>2, the year is defined as wet year. The explanatory variable DRY is the number of dry years during the previous four years; and the explanatory variable WET is the number of wet years during the previous two years.

Estimation Methods

The empirical model specified in equation (4) is estimated using pooled cross-sectional and time-series data. The traditionally i.i.d. assumption of the error term u_{it}^{m} is not appropriate for a panel data model. The error term might contain unobserved individual effect due to factors that are different across counties. We rewrite equation (4) as:

(5) $y_{it}^m = X_{it}\beta^m + \mu_i^m + v_{it}^m$

where, $y_{it}^m = \log(s_{it}^m / s_{it}^0)$ and $u_{it}^m = \mu_i^m + v_{it}^m$. Assume that μ_i^m is the unobserved individual effect which is independent of the v_{it}^m, and $v_{it}^m \sim iid(0, \sigma_v^2)$. The individual effect μ_i^m can be assumed to be either fixed parameters (fixed effects model) or random variables, i.e. $\mu_i^m \sim iid(0, \sigma_u^2)$ (random effects model).

The empirical model specified in equation (5) is a system of three share equations. It is highly possible that the choice of one type of tillage system affects the choice of other type of tillage. Therefore, contemporaneous correlation may exist across alternative tillage choice within the same county. Zeller's seemingly unrelated regression (SUR) techniques are widely used to correct such contemporaneous correlation problem. Standard SUR techniques can be directly applied to the fixed effects model, because the fixed effects model can simply be written as the linear regression with dummy variables (LSDV). In our model, as the explanatory variables are identical across equations, the SUR estimators applied to the set of equations are the same as the least square estimators applied to each equation separately. Therefore, the equations with fixed effects specification are estimated separately. However, for random effects model, when the same explanatory variables appear in each equation, GLS performed on the whole system is not equivalent to GLS performed on each equation separately (Baltagi 1980, Baltagi 2001, pp. 105-109).

We construct the SUR estimator with random-effects error component following Baltagi's method. First, run the within regression on each share equation to get the within-type residues:

(6) $\hat{U} = (\hat{u}^1, \hat{u}^2, \hat{u}^3)$

where $\hat{u}^m$ is the vector of residues from *m*-th equation. The variance-covariance matrix of the equation system is given by:

(7) $\Omega = \Sigma_1 \otimes P + \Sigma_v \otimes Q$

where $P = I_N \otimes \bar{J}_T$ and $Q = I_{NT} - P$. Σ_v and Σ_1 can be estimated by $\hat{\Sigma}_v = \hat{U}' Q \hat{U} / N(T-1)$ and $\hat{\Sigma}_1 = \hat{U}' P \hat{U} / N$, separately. The feasible GLS estimator of the set of equations with random-effects error component is then given by:

(8) $\hat{\beta}_{SUR-RE} = (X'\hat{\Omega}^{-1}X)(X'\hat{\Omega}^{-1}Y)$

Preliminary Results

Due to problems in data collection and computational difficulties, we have preliminary results for the state of Nebraska only. The results of the entire study region will be added to the text as soon as they are available. Since only one state's data are used, some estimates may be inaccurate due to limited cross-sectional variations.

The results from within regressions are presented in Table 3. The within-type residuals are use to construct the SUR-Random-Effects estimator using Baltagi's method described in the previous section. The estimated results are listed in Table 4.

The highly erodible land has positive impact on the adoption of all three tillage systems (no-till, ridge-mulch-till, and reduced till) compared to conventional till, however the effect is not significant in any equation. The land slope has no significant effects either. The share of cropland operated by renters has negative effects in all three equations as expected, but the coefficients are not significant. As the estimated coefficients of all three cross-sectional variables have expected signs but insignificant t-statistics, we expect that our results might improve after including data from other states.

Both dummy variables of farm bills show positive and significant effects on the adoption of no-till, and the 2002 farm bill seems to have stronger effect, which is consistent with our expectation. The percent of land planted to corn and soybean has positive and significant coefficients in all three equations. The estimated coefficients relating irrigated land are not consistent across tillage systems, although they are all significant. It is negative for no-till, but positive for other tillage systems. The reason of positive effects is perhaps that some tillage systems (like ridge-till) are compatible with certain irrigation systems (like furrow irrigation). Coefficients on farm numbers and CRP land are insignificant. All three coefficients relating the number of dry years are positive, but only the one on ridge-mulch-till is significant. On the other hand, all three coefficients relating the number of wet years are positive and significant except for reduced till. Our results suggest that weather extremes (either abnormally dry or wet conditions) did promote the adoption of conservation tillage, although drought impact on no-till adoption is insignificant.

Conclusion

A better understanding of how farmers adjust their production practices to cope with extremely wet or dry conditions is essential for developing effective drought mitigation policies and reducing the impact of other natural disasters. Reducing the risk associated with drought and flood in the long-run may be more cost effective than smoothing short-term income losses through disaster relief money. Most existing assistance programs focus on diversifying and stabilizing income risks through crop insurance and direct payments, however there are fewer efforts designed to reduce the long-term agricultural risk associated with drought events and expectations of high climate variability in the future due to climate change.

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Table 1. Definition of Variables

Variables	Definition
Dependent variables	
No-till	Share of no-till adopted in each county
Alternative conservation tillage	Share of ridge-till and mulch-till adopted in each county
Reduced tillage	Share of reduced tillage adopted in each county
Conventional tillage	Share of conventional adopted in each county
Explanatory variables	
Highly erodible land	Share of cropland with erodibility index greater than 8
Land slope	Weighted average land slope gradient
Cash-renter	Share of cropland operated by tenants
Fuel price	Annual price of liquefied petroleum gas
Policy instruments	
Yr_97	Yr_97=1, if year=1997~2001, else Yr_97=0
Yr_02	Yr_02=1, if year=2002~2004, else Yr_02=0
Corn-soybean percent	Percent of cropland planted to corn and soybean
Irrigated land percent	Percent of irrigated cropland
Farm number	Number of farms
CRP land percent	Percent of cropland enrolled to Conservation Reserve Program
DRY	Number of dry years
WET	Number of wet years

Table 2. Palmer Classifications

4.0 or more	extremely wet
3.0 to 3.99	very wet
2.0 to 2.99	moderately wet
1.0 to 1.99	slightly wet
0.5 to 0.99	incipient wet spell
0.49 to -0.49	near normal
-0.5 to -0.99	incipient dry spell
-1.0 to -1.99	mild drought
-2.0 to -2.99	moderate drought
-3.0 to -3.99	severe drought
-4.0 or less	extreme drought

Source: National Drought Mitigation Center

Table 3. Within estimates of county-level share equations for Nebraska

Variables	No-till	Alternative conservation tillage	Reduced tillage
Intercept	-3.431	-3.946	-3.225
	(-1.7)	(-2.13)	(-1.78)
Highly erodible land			
Land slope			
Cash-renter			
Yr_97	0.374	-0.152	-0.303
	(2.28)	(-1.04)	(-2.06)
Yr_02	0.67	-0.429	-0.678
	(2.85)	(-1.93)	(-3.12)
Corn-soybean percent	2.893	3.687	2.633
	(3.31)	(4.6)	(3.36)
Irrigated land percent	-1.146	1.912	3.564
	(-1.26)	(2.29)	(4.36)
Farm number	-0.002	-0.0002	-0.002
	(1.02)	(-0.14)	(-1.33)
CRP land percent	5.557	0.771	-4.545
	(1.41)	(0.21)	(-1.29)
DRY	0.149	0.187	0.013
	(0.19)	(2.58)	(0.19)
WET	0.382	0.227	0.057
	(4.77)	(3.08)	(0.79)

* Numbers in parentheses are t-statistics

Table 4. SUR-Random-Effects estimates of county-level share equations for Nebraska

Variables	No-till	Alternative conservation tillage	Reduced tillage
Intercept	0.717 (0.313)	-2.666 (-2.044)	-0.521 (-0.281)
Highly erodible land	0.232 (0.136)	0.82 (0.872)	2.118 (1.54)
Land slope	0.017 (0.162)	0.056 (0.98)	-0.019 (-0.222)
Cash-renter	-15.64 (-1.44)	-2.10 (-0.34)	-10.503 (-1.199)
Yr_97	0.3 (2.0)	-0.141 (-1.11)	-0.24 (-1.825)
Yr_02	0.651 (3.256)	-0.42 (-2.598)	-0.529 (-3.044)
Corn-soybean percent	3.23 (4.377)	3.318 (6.151)	2 (3.177)
Irrigated land percent	-1.332 (-1.838)	1.902 (3.837)	2.501 (4.10)
Farm number	-0.001 (-1.174)	-0.0007 (-1.201)	-0.0007 (-0.81)
CRP land percent	0.988 (0.314	1.282 (0.585)	-0.463 (-0.174)
DRY	0.019 (0.25)	0.171 (2.439)	0.0124 (0.179)
WET	0.389 (4.896)	0.233 (3.216)	0.05 (0.707)

* Numbers in parentheses are t-statistics