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The Impact of Weather Extremes on Agricultural Production Methods: Does Drought Increase Adoption of Conservation Tillage Practices?

Ya Ding, Karina Schoengold, and Tsegaye Tadesse

The paper combines panel data techniques with spatial analysis to measure the impact of extreme weather events on the adoption of conservation tillage. Zellner's SUR technique is extended to spatial panel data to correct for cross-sectional heterogeneity, spatial autocorrelation, and contemporaneous correlation. Panel data allow the identification of differences in adoption rates. The adoption of no-till, other conservation tillage, and reduced-till are estimated relative to conventional tillage. Extremely dry conditions in recent years increase the adoption of other conservation tillage practices, while spring floods in the year of production reduce the use of no-till practices.

Key words: conservation tillage, drought, panel data, technology adoption, weather extremes

Introduction

Each year, 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 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, Marsh, and Marshall, 2006). 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, and 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 these difficulties. A significant amount of economic literature provides recommendations on how the suite of federal crop insurance and disaster payment programs can be improved (see Glauber, 2004,

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Ya Ding is a post-doctoral researcher with the National Drought Mitigation Center at the University of Nebraska; Karina Schoengold is an assistant professor with the Department of Agricultural Economics and the School of Natural Resources, the University of Nebraska; and Tsegaye Tadesse is an assistant professor and climatologist with the National Drought Mitigation Center at the University of Nebraska. The authors gratefully acknowledge the financial support provided by the USDA/RMA Partnership Agreement No. 02-IE-0831-0228 with the University of Nebraska-Lincoln, and the University of Nebraska Agricultural Research Division. The authors would also like to acknowledge the assistance of participants at the 2007 AAEA annual conference and the 2007 Heartland Environmental and Resource Economics workshop, and helpful comments from the editor and two anonymous reviewers.

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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 rise because of climate change and increased occurrences of extreme weather events such as floods and droughts (Frederick and Schwarz, 2000). However, the adoption of agricultural conservation practices, such as no-tillage production (no-till), is one strategy farmers can use to protect themselves against such events.

During a recent multi-year drought, we observed increasing adoption levels of no-till in the drought-stricken area. According to the Conservation Tillage Information Center (2007), the national level of no-till farmland increased 38% from 1998 to 2006, while the drought-impacted states of Nebraska, South Dakota, and Kansas saw an increase of 67% over this same period. 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 is a production method of growing crops from year to year without plowing the soil, a practice resulting in increased levels of crop residues in the field. Because no-till conserves soil moisture, its adoption is one strategy agricultural producers can use to reduce their risk associated with drought. We hypothesize that farmers' experience during past droughts would change their expectations of future weather risk and water availability, and thus affect their investment decision in conservative tillage practices.

Previous Research

A sizable literature has studied the factors influencing farmers' adoption of conservation tillage systems. Ervin and Ervin (1982) summarized those factors into four categories: physical, economic, personal, and institutional. Agronomic studies have investigated a variety of physical determinants governing the success or failure of conservation tillage in terms of yield response and erosion control. The identified factors include soil properties, land slope, climate condition, and cropping systems (Amemiya, 1977; Fenster, 1977; Phillips et al., 1980; Cosper, 1983; Norwood, 1999). Generally, the experimental results suggest that no-till, when applied on suitable land with favorable weather and proper management, could produce yields at least as high as conventional tillage.

The economic feasibility of conservation tillage practices has been evaluated with consideration of financial constraints and risk preference of farmers. Budgeting procedures and mathematical programming were often employed to compare the expected profit or utility under alternative tillage systems. Factors investigated in these studies include farm income, adjustment costs, planning horizon, government programs, and risk aversion (Epplin et al., 1982; Helms, Bailey, and Glover, 1987; Williams, 1988; Williams, Llewelyn, and Barnaby, 1990; Krause and Black, 1995). Some studies considered conservation tillage to be riskier than conventional tillage, and therefore concluded that risk-averse producers are less likely to adopt conservation tillage systems. The perceived risk of conservation tillage is mainly a result of unfamiliarity with the new tillage practices or lack of management skills. This perception should decrease over time with education, demonstration, and assimilation of the new technology.

In addition to the physical and economic factors described above, many econometric studies have also examined the impact, magnitude, and significance of personal and/or institutional variables. Lee and Stewart (1983) and Soule, Tegene, and Wiebe (2000) analyzed the relationship between farm size, land ownership, and the adoption of conservation practices.

Ervin and Ervin (1982), Rahm and Huffman (1984), Gould, Saupe, and Klemme (1989), and Wu and Babcock (1998) have investigated the role of human capital (such as education and experience) in decisions to adopt conservation practices. Kurkalova, Kling, and Zhao (2006) estimated the green subsidies required for achieving certain adoption rates for conservation tillage.

Previous econometric analyses often employed cross-sectional data to assess the adoption decision in response to site-specific information. One limitation of using cross-sectional data is that it is impossible to identify the effects of those variables that change over time but present little cross-sectional variation for a given time period, such as prices, weather, and policy variables. Previous studies have measured the effect of cross-sectional long-term climate variables (e.g., 30-year averages for precipitation, temperature, and growing degree days) on tillage adoption, although some estimated results were not significant (Rahm and Huffman, 1984; Soule, Tegene, and Wiebe, 2000). Because of the limitations of using cross-sectional data, previous research did not consider the impacts on tillage practices of short-term or mid-term weather extremes. We expect that the effects on tillage practices of recent weather extremes would be at least as significant as long-term climate trends. To test this theory, we use panel data of pooled cross-sectional and time-series information in the study.

This paper's objective is to estimate the impact of recent precipitation shocks (i.e., drought and flood) on the adoption of conservation tillage systems. We use econometric analysis and panel data to model the adoption of alternative tillage systems over years. Our study contributes to the literature in several ways: (*a*) we use panel data to account for both cross-sectional and temporal effects, (*b*) we employ two types of drought index to account for both short-term and mid-term precipitation shocks, and (*c*) we incorporate spatial analysis into the study of tillage choices. The remainder of the paper is organized as follows. We first develop the empirical model and describe the estimation method. We then explain variables entering the regression model and discuss the estimated results. The final section summarizes our findings and gives concluding remarks.

Empirical Model Development

We assume that producers choose a certain type of tillage practice based on their characteristics and expectations about weather during the following season. A tillage practice is chosen before planting for a single season, and that choice is reversible in the future. Based on agronomic reasons, profit levels under conventional tillage practices are assumed to be more affected by weather conditions than profit levels with conservation practices. Conservation tillage practices increase soil moisture, thereby reducing the risk associated with bad weather. This is important, as it allows us to predict the effect of changes in weather expectations on the adoption of conservation tillage.

Based on observations from county-level data, we assume that heterogeneity in land quality, crop choice, and other characteristics means we will generally observe a mix of conventional and conservation tillage practices. The share of land in each alternative will change over time because of government programs, education, and increasing awareness, but we expect to continue to see land in a variety of tillage practices.

If producers' expectations of weather are constant over time, then they will choose the tillage practice that maximizes their expected profit. If those expectations are based on historical averages, and are not updated after recent weather events, then the shares of each tillage practice would be expected to remain relatively constant over time, conditional on other

explanatory variables (e.g., government subsidy programs, increased acceptance and learning about conservation tillage). However, in this paper we hypothesize that producers do change their expectations about weather over time, and that recent weather events are significant in forming those expectations. We hypothesize that producers are myopic in their decisions, and recent droughts and floods impact their choice of tillage more than long-term average weather conditions. Therefore, producers who endure several years of drought will adjust their expectations of weather conditions accordingly. With a change in the expectation about weather conditions, the shift in expected profits under conventional tillage is impacted more than the shift in expected profits under conservation tillage.

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 intertemporal factors. The maximization problem can be written as:

$$\Pi = \underset{s^m}{\text{Max}} \sum_m (s^m \pi^m) \quad \text{s.t.}: \sum s^m = 1, \tag{1}$$

where π^m is the profit and s^m is the share of land planted with the mth tillage method. Previous studies on the choice of tillage systems often employed a multinomial logit adoption model using field-level data (Soule, Tegene, and Wiebe, 2000; Wu and Babcock, 1998; Kurkalova, Kling, and Zhao, 2006). However, because of the absence of time-series information at the field level, county-level data are the most disaggregated data available. Therefore, the county average values of land shares, weather conditions, site attributes, and other economic variables are used in this study.

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:

$$s_{it}^m = \frac{e^{\mathbf{X}_{it}\boldsymbol{\beta}^m}}{\sum_{m=0}^{M} e^{\mathbf{X}_{it}\boldsymbol{\beta}^m}}, \tag{2}$$

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

$$\log(s_{it}^m / s_{it}^0) = \mathbf{X}_{it}\boldsymbol{\beta}^m + \mathbf{u}_{it}^m, \tag{3}$$

where $\boldsymbol{\beta}^m$ is the vector of coefficients to be estimated, and $\mathbf{u}_{it}^m$ is the vector of error components. The vector of explanatory variables, $\mathbf{X}_{it}$, includes three types of variables: (*a*) cross-sectional and time-invariant variables, like land characteristics; (*b*) time-series variables, which present little cross-sectional variation, such as prices; and (*c*) cross-sectional and time-series data, such as cropping patterns and weather extremes.

The model specified in equation (3) is estimated using pooled cross-sectional and time-series data. The traditionally i.i.d. assumption of the error term $\mathbf{u}_{it}^m$ is not appropriate for a panel data model. The error term might contain a heterogeneous individual effect because of factors that differ across counties. In addition, spatial autocorrelation is likely to be present

given that county-level data are used, and omitted variables may simultaneously affect all neighboring counties.[1] In this study, we combine panel data with spatial analysis. Furthermore, our empirical model resulting from the land allocation problem contains multiple equations. Because unobserved common factors may influence alternative tillage practices in the same county and year, contemporaneous correlation likely exists across equation errors. Zellner's (1962) seemingly unrelated regression (SUR) techniques are widely used to correct such contemporaneous correlation problems. Here, we extend Zellner's SUR technique to the spatial panel model. The following three-step procedure is proposed to account for cross-sectional heterogeneity, spatial autocorrelation, and contemporaneous correlation.

First, we reconstruct the error term to incorporate the random county effects as well as the spatial autocorrelation, following Baltagi (2001, pp. 195–197). Equation (3) is rewritten as:

$$y_{it}^m = \mathbf{X}_{it}\boldsymbol{\beta}^m + u_{it}^m, \quad i = 1, ..., N;\ t = 1, ..., T;\ m = 1, 2, 3, \tag{4}$$

where $y_{it}^m = \log(s_{it}^m / s_{it}^0)$ is the observation of the mth tillage system in county i at time t, and u_{it}^m is the error term. Equation (5) shows how random effects are incorporated into the error term, and equation (6) extends the random effects model to include spatial error autocorrelation:

$$\mathbf{u}_t^m = \boldsymbol{\mu}^m + \boldsymbol{\varepsilon}_t^m \tag{5}$$

and

$$\boldsymbol{\varepsilon}_t^m = \lambda^m \mathbf{W}\boldsymbol{\varepsilon}_t^m + \mathbf{v}_t^m \quad \rightarrow \quad \boldsymbol{\varepsilon}_t^m = (\mathbf{I}_N - \lambda^m \mathbf{W})^{-1}\mathbf{v}_t^m = \mathbf{B}^{-1}\mathbf{v}_t^m, \tag{6}$$

where $\boldsymbol{\mu}^m = (\mu_1^m, ..., \mu_N^m)'$ denotes the vector of random individual effects, and $\boldsymbol{\mu}_i^m \sim \text{iid}(0, \sigma_u^{m2})$. $\mathbf{W}$ is the $N \times N$ weight matrix representing the spatial relationship across counties, and λ^m is the corresponding spatial autocorrelation coefficient for equation m. Here, $\mathbf{W}$ is defined as a symmetric contiguous matrix, where each element $\{w_{ij}\}$ equals 1 if county i is adjacent to county j, and 0 otherwise; $\mathbf{v}_t^m = (v_{1t}^m, ..., v_{Nt}^m)$, where $v_{it}^m \sim \text{iid}(0, \sigma_v^{m2})$ and independent of the $\boldsymbol{\mu}_i^m$. $\mathbf{I}_N$ is an $N \times N$ identity matrix.

Equation (4) can be rewritten in matrix form as:

$$\mathbf{Y}^m = \mathbf{X}\boldsymbol{\beta}^m + \mathbf{u}^m, \quad \text{with } \mathbf{u}^m = (\mathbf{l}_T \otimes \mathbf{I}_N)\boldsymbol{\mu}^m + (\mathbf{I}_T \otimes \mathbf{B}^{-1})\mathbf{v}^m, \tag{7}$$

where $\mathbf{l}_T$ is a $T \times 1$ vector of ones, and $\mathbf{I}_T$ is a $T \times T$ identity matrix. The variance-covariance matrix of $\mathbf{u}^m$ is given by:

$$\boldsymbol{\Omega}^m = E(\mathbf{u}^m\mathbf{u}^{m\prime}) = \boldsymbol{\sigma}_\mu^{m2}(\mathbf{l}_T\mathbf{l}_T' \otimes \mathbf{I}_N) + \boldsymbol{\sigma}_v^{m2}\left(\mathbf{I}_T \otimes (\mathbf{B}'\mathbf{B})^{-1}\right). \tag{8}$$

The estimation of equation (7) follows the procedure provided by Elhorst (2003), who gave comprehensive guidance on how to combine panel data with spatial autocorrelation. Each share equation is estimated separately.

Next, we use the estimated $\widehat{\sigma}_\mu^m$, $\widehat{\sigma}_v^m$, and $\widehat{\lambda}^m$ to make the transformations on the dependent and explanatory variables to correct for spatial autocorrelation and random effects:[2]

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[1] For an introduction to the spatial models, see Anselin (1988).

[2] See Elhorst (2003) for the details of the transformations.

$$Y^{m*} = \mathbf{X}^{m*}\boldsymbol{\beta} + e^{m}, \quad m = 1, 2, 3, \tag{9}$$

where Y^{m*} and $\mathbf{X}^{m*}$ are the transformed dependent and explanatory variables, and the transformed error term $e^{m} \sim \text{iid}(0, \sigma^{m2})$.

Finally, we apply the standard SUR techniques to the system of equations specified in (9) to correct for contemporaneous correlation across equation errors. The three-step estimation procedure is implemented using MATLAB. The estimated results are discussed in the following section.

Data and Variables

In this study, we estimate the empirical model using county-level data from Iowa, Nebraska, and South Dakota. In each of these states, significant acreage is planted with no-till or other conservation tillage methods, and the adoption rate continues to increase (see figure 1 for no-till acreage by each state). Large areas of Nebraska and South Dakota have experienced severe multi-year drought since 2000, but most of Iowa has not been affected by the drought. Accordingly, these three states make a good study region for analyzing the effect of weather extremes on the adoption of no-till. Because of data set size limitations, we are unable to use the entire sample. Additionally, since county-level data are used and the shares instead of the acres of tillage systems are the dependant variables, we want to include those counties with extensive cropland in order to obtain representative results. Therefore, we chose to include those counties with at least 60% of the land area cultivated.[3] The variables selected for analysis and their definitions are summarized in table 1. Detailed descriptions of variables and data sources are presented below.

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, 2007).[4] By the most commonly used definition, conservation tillage is referred to as any tillage system that leaves at least 30% 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% residue), and conventional till (less than 15% 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 denoted "other conservation till." Thus, four categories of tillage systems are analyzed in the empirical model. We chose conventional till as the base category; consequently, three share equations are estimated after normalization (i.e., $M = 3$).

Explanatory Variables

The selection of explanatory variables is based on previous studies as well as our hypotheses. Some previously identified factors are not included in the explanatory function for two reasons. First, for some variables like farm size and land tenure, whose values change over

[3] We ran the same analysis for various threshold levels, and the general significance and size of the results are unchanged.

[4] The CRM survey was conducted annually from 1990 to 1998; after 1998, it was conducted biennially.

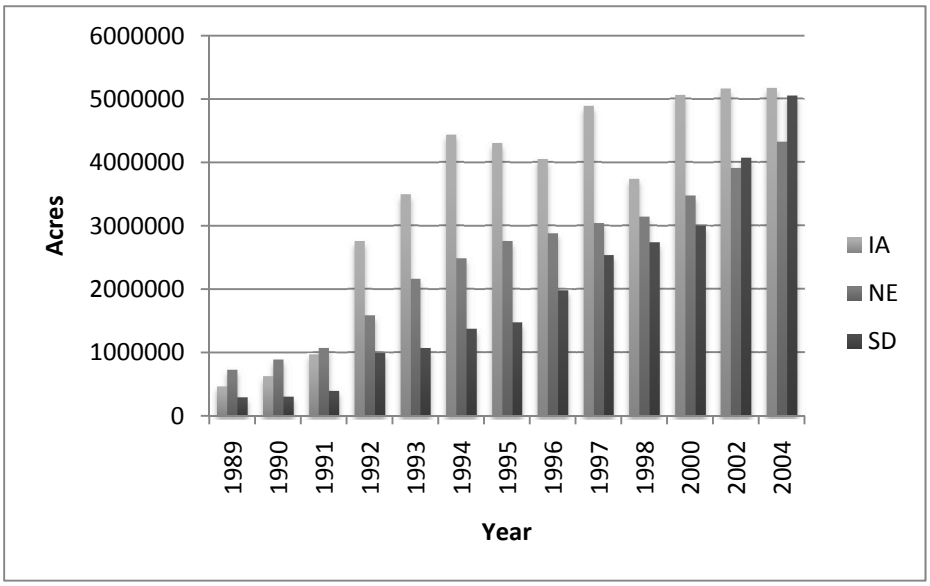

Figure 1. No-till acreage by state, 1989–2004

Table 1. Description of Variables and Summary Statistics

Variable	Definition	Mean	Std. Dev.
Dependent Variables:			
No-till	Share of no-till adopted in each county	0.183	0.160
Other Conservation Tillage	Share of ridge-till and mulch-till adopted in each county	0.322	0.161
Reduced Tillage	Share of reduced tillage adopted in each county	0.277	0.109
Conventional Tillage	Share of conventional tillage adopted in each county	0.217	0.147
Explanatory Variables:			
PDSI_Dry	Number of dry years in the last five years	0.897	1.050
PDSI_Wet	Number of wet years in the last five years	0.803	0.866
SPI_Wet	1 if SPI > 1.5, otherwise 0	0.054	0.227
Precipitation	30-year average annual precipitation	30.019	5.044
Temperature	30-year average temperature of February–April	34.817	4.075
Corn-Soybean %	Share of cropland planted to corn and soybeans	0.875	0.190
Highly Erodible Land	Share of land with erodibility index greater than 8	0.263	0.207
Fuel Price	Price of motor gasoline ($/mil. BTU in 2000 $)	10.498	1.141
Insured Cropland	Share of cropland enrolled in crop insurance program	0.553	0.215
T	Time trend variable (T = 1, 2, ...)	8.000	4.204
T^2	Time trend variable squared	81.667	76.388

the years, county-level data are not available for each year. Second, there is very limited variation in the county average values of some variables, such as education, age, and farming experience of operators, making the identification of their effect on tillage choice impossible.

Cross-Sectional, Time-Invariant Variables

■ *Highly Erodible Land* (*HEL*): Following the same definition used by the Natural Resources Conservation Service, highly erodible land is defined as land having an erodible index greater than 8. Since reducing soil erosion is a major benefit associated with conservation tillage, operators farming on highly erodible land are more likely to adopt conservation tillage practices. In addition, certain government programs require the participants to use conservation practices on highly erodible land to receive commodity payments and other program benefits. The data are obtained from the USDA/National Resources Conservation Service (NRCS) (2007) SSURGO Soils Database. To provide a consistent comparison across counties of varying sizes, we use the percentage of cropland designated as HEL as an explanatory variable.

■ *Precipitation*: Greater amounts of crop residue left on the soil surface significantly reduce water evaporation and increase water infiltration into the soil. This advantage makes conservation tillage a more desirable choice for farmers normally receiving lower precipitation levels. We expect a negative relationship between adoption of conservation tillage systems and precipitation levels. The 30-year (1970–2000) average annual precipitation is included in the explanatory function.

■ *Temperature*: The mulching effect of crop residues reduces soil temperature, and the lower soil temperature might delay spring planting and early growth of plants. This disadvantage of conservation tillage is a serious concern in areas where soil temperature is normally below the optimum for crop growth during the early growing season.[5] However, some researchers argue that the adoption of conservation tillage should be greater in areas with a shorter growing season because conservation tillage systems reduce fieldwork during the critical pre-plant and post-harvest periods (Rahm and Huffman, 1984). Therefore, the negative effect of crop residues on soil temperature might be offset by the time-saving effect of conservation tillage systems. For these reasons, the effect of temperature on the tillage practices is unclear. In this study, the 30-year (1970–2000) average temperature of February through April is used to measure the effect of spring temperature on tillage adoption.

Time-Series Variables

■ *Fuel Price*: The increasing fuel prices in recent years could be an important driving force in the adoption of no-till, as no-till reduces the machinery-related costs and fuel consumption. The state-level motor gasoline prices are used in this study. The price data are obtained from the U.S. Department of Energy/Energy Information Administration (DOE/EIA, 2007).[6]

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[5] The lower soil temperature can be advantageous in the tropics where the soil temperature is usually above the optimum for plant growth (Phillips et al., 1980).

[6] Alternative fuel prices were also considered in the analysis, but the various prices are so highly correlated that we chose a single indicator.

■ *Time Trend Variables:* A time trend (T) and a squared time trend (T^2) variable are included to capture temporal effects such as changes in technology, policy, and general farmer acceptance of conservation practices. These are factors which are not explained by the other intertemporal variables in the explanatory function. With the development of machinery, equipment, and management skills suitable for no-till practices, we expect the costs of no-till to decrease over the years; meanwhile, the long-term benefits of no-till have been demonstrated. Additionally, recent changes in government programs have given more incentives to farmers to adopt no-till and other conservative tillage methods. For example, the Environmental Quality Incentives Program, enacted in 1996 and expanded in 2002, provides financial incentives and technical assistance to farmers who are willing to adopt conservation tillage. Other state and local programs have also been developed to provide such incentives. We hypothesize that the adoption rate of no-till is increasing over time, which implies a positive coefficient of the time trend variable.

The coefficient on the time-squared variable is unclear and depends on whether the adoption rate of no-till increases at an increasing rate or a decreasing rate. Since the seminal work of Griliches (1957), the technology adoption literature has shown that the level of adoption follows an S-shaped curve, as depicted in figure 2. If we denote the technology adoption rate by A, figure 2 shows that there is a time $\hat{t}$, where for $t < \hat{t}, \partial^2 A / \partial t^2 > 0$; and for $t > \hat{t}, \partial^2 A / \partial t^2 < 0$. For a technology that is very new, we would expect the coefficient on this term to be positive. However, conservation tillage practices have been known for decades, and therefore we are not sure of the sign of the coefficient. We will be able to test this in the empirical results.

Cross-Sectional and Time-Series Variables

■ *Corn and Soybeans*: The data suggest that conservation tillage is more frequently adopted with the production of corn and soybeans. One proposed explanation suggested is that conservation tillage provides greater benefits with corn and soybeans than with other crops. First, corn and soybeans are water-intensive crops and lack drought tolerance (Norwood, 1999). Second, corn takes longer than other crops to establish groundcover in the spring, when the land is most prone to soil erosion. Since a corn-soybean rotation is widely adopted in our study region, we incorporate the percentage of corn and soybean land into the explanatory function.

■ *Crop Insurance Program*: Since 1980, the Federal Crop Insurance Program has become the primary form of crop loss protection for agricultural producers in the United States. To encourage participation, the insurance premiums are highly subsidized. According to the 2007 report of the Risk Management Agency (USDA, Office of Inspector General, 2007), approximately 60% of total premiums were paid by the federal government. The high level of subsidies has raised concerns about the potential distorting effects of the crop insurance program on farmers' production decisions. Previous research suggests that crop insurance plays a role in determining input use, planted acres, and cropping patterns (Smith and Goodwin, 1996; Babcock and Hennessy, 1996; Wu, 1999; Goodwin, Vandeveer, and Deal, 2004). Williams (1988) and Wu and Babcock (1998) have analyzed the effect of crop insurance on tillage practices, but their results were inconclusive as to whether crop insurance programs promote or delay the adoption of conservation tillage. In this paper, we include the percentage of acres insured in each county as an explanatory variable to determine its effect on the adoption decision of alternative tillage methods.

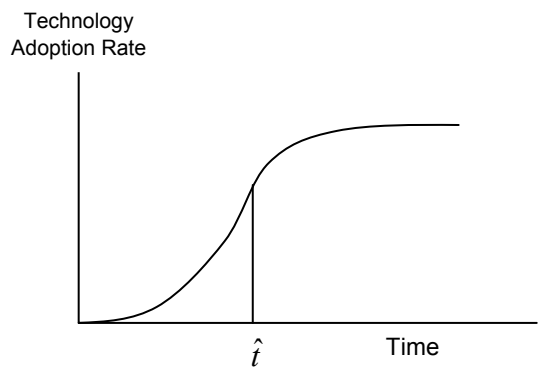

Figure 2. Technology adoption rate over time

■ *Weather Extremes*: As mentioned earlier, previous studies have measured the role of long-term climate patterns in the adoption decision of a tillage system; the recent occurrence of weather extremes also might be an influencing factor for producers. In this study we construct the weather extreme variables using two types of drought indices: the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI).

The PDSI is one of the most commonly used drought indices in the United States. It represents the soil moisture condition for an area by implementing a water balance equation (Palmer, 1965; Keyantash and Dracup, 2002). The PDSI value is an indicator of how climate conditions compare to long-term average conditions for an area. It is calculated based on parameters including precipitation, temperature, and soil moisture levels. The PDSI calculation builds on the past values of precipitation and temperature, so that the value at a particular time is based on a combination of current conditions and previous values. Thus, this drought indicator reflects the progression of climate trends (i.e., whether it is a dry or a wet spell). The value of the PDSI usually varies between −4.0 and 4.0, with a negative number indicating abnormally dry and a positive number indicating abnormally wet. The PDSI classifications are listed in table 2.

Because crop residue cover traps soil moisture, no-till and other conservation till are methods producers can use to reduce their risk associated with drought; therefore, more adoption of conservation till is expected to occur after a multiple-year drought. In contrast, rain is the predominant cause of soil erosion. Heavy rainstorms contribute to soil erosion and destructive damage. Without any shift in production practices, wet years can significantly increase soil loading into surface water sources (Turvey, 1991). An effective method to fight this type 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 in recent growing seasons would affect farmers' willingness to adopt no-till or other conservation tillage systems. In our empirical model, the August PDSI is used to measure the moisture condition of the previous growing season. We chose to use the August PDSI because it is a good indicator of dryness for the past growing season. Unlike cropping decisions, which can be changed any time before planting in early spring, farmers generally choose their tillage practice immediately after harvest.

The PDSI data were obtained from the High Plains Regional Climate Center (HPRCC) for each weather station within the study area. The station-level data are then aggregated to

Table 2. PDSI Drought Index Classifications

Index Value	Description		Index Value	Description
4.0 or more	Extremely wet		−0.5 to −0.99	Incipient dry spell
3.0 to 3.99	Very wet		−1.0 to −1.99	Mild drought
2.0 to 2.99	Moderately wet		−2.0 to −2.99	Moderate drought
1.0 to 1.99	Slightly wet		−3.0 to −3.99	Severe drought
0.5 to 0.99	Incipient wet spell		−4.0 or less	Extreme drought
0.49 to −0.49	Near normal			

Source: National Drought Mitigation Center.

Table 3. SPI Drought Index Classifications

Index Value	Description		Index Value	Description
2.0 or more	Extremely wet		−1.0 to −1.49	Moderately dry
1.5 to 1.99	Very wet		−1.5 to −1.99	Severely dry
1.0 to 1.49	Moderately wet		−2.0 or less	Extremely dry
−0.99 to 0.99	Near normal			

Source: National Drought Mitigation Center.

represent each county using Arc Map Geographic Information System (GIS) techniques. Some threshold values are needed to specify an extreme year (either abnormally dry or abnormally wet). By Palmer's (1965) classification, PDSI values below −2 indicate moderate drought, and PDSI values greater than 2 indicate moderately wet conditions. However, Wells, Goddard, and Hayes (2004) caution that the actual values of the historical PDSI value distribution do not fit the normal distribution centered with zero mean. Our PDSI data in the study area have also shown right-skewed distribution of PDSI with positive mean. Thus, the PDSI classification is adjusted accordingly. With empirical adjustment, we set the threshold values at −1.5 and 2.5, respectively. Specifically, if the PDSI is below −1.5, the year is defined as a dry year; if the PDSI is above 2.5, the year is defined as a wet year. The explanatory variable *PDSI_Dry* is the number of dry years during the previous five years, and the explanatory variable *PDSI_Wet* is the number of wet years during the previous five years.

SPI is also a widely used drought index in the United States. It is calculated based on the probability of precipitation for any time scale. The advantage of the SPI is that it quantifies precipitation anomalies for multiple time scales. Compared to the PDSI, the SPI is more efficient in measuring short-term precipitation variation. Similar to the PDSI, a negative value of the SPI indicates abnormally dry conditions, while a positive value indicates abnormally wet conditions. The SPI values are listed in table 3.

Cold and wet soil immediately before planting in spring is a critical deterrent to the use of conservation tillage systems. Surface crop residues delay soil warming and drying. Additionally, long-term intensive tillage causes soil compaction, and excessive rain would worsen the problem of compaction. Although long-term continuous no-till solves, rather than causes, the compaction problem, it is challenging for first-timers to use no-till on previously compacted soils. Producers who were originally planning to use no-till might need to change their plans

after a very wet spring. Anecdotal evidence suggests some farmers blamed the compaction problems on no-till, and eventually abandoned no-till practices. We do not include an *SPI_Dry* variable in the estimation because the agronomic evidence suggests that a dry season immediately before planting will not change a producer's planned tillage practice. Consequently, there is no reason to include an *SPI_Dry* variable, as the *PDSI_Dry* variable captures the effects of recent drought conditions.

The April three-month SPI is used to measure the precipitation anomalies during the springtime. The SPI data for each weather station within the study area were obtained from the HPRCC. The station-level data are then aggregated to represent each county using Arc Map GIS techniques. A dummy variable, *SPI_Wet*, is constructed using the county-level SPI. *SPI_Wet* is set equal to 1 if the value of SPI is greater than 1.5, indicating a very wet spring; otherwise, it is set equal to 0. We expect a negative effect of *SPI_Wet* on the adoption of no-till.

Estimation Results and Discussion

The estimated coefficients of explanatory variables as well as the spatial autocorrelation coefficients are reported in table 4. The estimated spatial autocorrelation coefficients are positive and significant in the no-till and other conservation-till equations, implying strong spatial correlations on the adoption of conservation tillage systems between neighboring counties. In addition to the coefficients, the marginal effects of explanatory variables on alternative tillage systems are also derived and reported in table 5.[7] It is well known that the coefficients in a multinomial logit model do not represent the true marginal effects of explanatory variables. Therefore, our interpretation of results is based on the values and significance levels of the marginal effects. Notice that the marginal effects on the adoption of no-till are all in opposite signs to those of reduced-till. This result implies the adoption of reduced tillage is probably not distinct from the conventional till, and is practiced as a transition between the conventional till and no-till.

The marginal effect of *PDSI_Dry* is positive for the adoption of no-till and other conservation tillage, while negative for the adoption of reduced tillage. This result is consistent with our expectation that farmers experiencing growing season drought in the recent past are more likely to adopt conservation tillage systems. However, the effect is not significant for the adoption of no-till. This finding may suggest that although farmers have a tendency to increase the no-till adoption after drought, they choose other conservation tillage systems as an intermediate step because no-till requires more management skills, initial investment, and changes to their existing operations.

The marginal effect of *PDSI_Wet* is not significant for the adoption of any tillage systems, suggesting abnormally wet conditions during the past growing seasons have minimal influence on farmers' choices of tillage practices. In contrast, the marginal effect of *SPI_Wet* shows a significantly negative effect on the adoption of no-till, which confirms our expectation that a very wet spring poses a serious obstacle to the use of conservation tillage. Although we assume the adoption decision is made right after the harvest of the previous season, excessive precipitation during the spring would cause difficulties to no-tillers, especially the first-timers. Some of them might be forced to give up the no-till practice under such circumstances. Conservation tillage must be practiced continuously for several years to

[7] See Greene (2000, p. 861) for the estimation of the marginal effects and the standard errors.

Table 4. Estimated Coefficients for Alternative Tillage Systems

	No-Till		Other Conservation Tillage		Reduced-Tillage	
Variable	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
Intercept	−7.088***	−5.329	−1.760	−1.510	1.079	1.325
PDSI_Dry	0.116*	1.645	0.137**	2.147	0.005	0.102
PDSI_Wet	0.073	1.022	0.048	0.743	−0.018	−0.354
SPI_Wet	−0.554***	−2.615	−0.362*	−1.940	−0.217	−1.510
Precipitation	−0.009	−0.377	−0.037	−1.704	−0.031**	−2.287
Temperature	0.016	0.768	0.021	1.091	−0.002	−0.163
Corn-Soybean %	1.418***	2.934	1.814***	4.133	0.896***	3.046
Highly Erodible Land	2.554***	4.678	0.332	0.672	0.435	1.413
Fuel Price	0.059	0.838	−0.035	−0.585	−0.084*	−1.876
Insured Cropland	−1.233***	−2.872	−0.334	−0.875	−0.146	−0.522
T	0.922***	10.097	0.258***	3.311	0.060	1.018
T^2	−0.036***	−7.275	−0.009**	−2.155	0.000	0.058
Spatial autocorrelation coefficient	0.219***	7.392	0.082**	2.548	0.024	0.653

Note: Critical values of *t* are 2.576, 1.960, and 1.645 at the 1%, 5%, and 10% levels, and are denoted by ***,**, and *, respectively.

Table 5. Estimated Marginal Effects for Alternative Tillage Systems

	No-Till		Other Conservation Tillage		Reduced-Tillage	
Variable	Marginal Effect	*t*-Statistic	Marginal Effect	*t*-Statistic	Marginal Effect	*t*-Statistic
PDSI_Dry	0.009	1.093	0.023**	2.179	−0.017*	−1.936
PDSI_Wet	0.009	1.076	0.008	0.745	−0.011	−1.282
SPI_Wet	−0.051**	−2.033	−0.027	−0.899	0.017	0.662
Precipitation	0.002	0.853	−0.005	−1.328	−0.003	−0.828
Temperature	0.001	0.521	0.004	1.206	−0.003	−1.136
Corn-Soybean %	0.060	1.042	0.232***	3.151	−0.054	−0.879
Highly Erodible Land	0.341***	5.060	−0.117	−1.440	−0.072	−1.034
Fuel Price	0.015*	1.840	−0.003	−0.369	−0.017**	−2.050
Insured Cropland	−0.158**	−3.100	0.013	0.211	0.063	1.189
T	0.120**	9.183	−0.003	−0.268	−0.058***	−5.160
T^2	−0.005**	−7.448	0.000	0.186	0.003***	4.485

Note: Critical values of *t* are 2.576, 1.960, and 1.645 at the 1%, 5%, and 10% levels, and are denoted by ***,**, and *, respectively.

improve soil properties. Tearing up the no-till field would destroy all the benefits accumulated. Education programs and technical assistances are needed to help farmers overcome difficulties in the early stages of practicing no-till.

The long-term average climate variables, *Precipitation* and *Temperature*, show no significant effects on the adoption of any tillage systems. This result is not surprising as some previous studies also reported insignificance. The lack of significance of the long-term climate variables confirms our hypothesis that the long-term climate information plays a minor role in the adoption decision of no-till in our study area.

Adoption rates of no-till are positively but insignificantly affected by cropping patterns, while adoption rates of other conservation tillage systems are significantly higher on land planted to corn and soybeans. Not surprisingly, no-till is adopted more frequently on highly erodible land, given that reducing soil erosion is one major benefit of no-till farming. Although adoption rates of other conservation tillage are negatively affected by the share of highly erodible land, the effect is not statistically significant.

Higher fuel prices significantly increase the adoption rates of no-till, while decreasing the adoption rates of reduced-till. This result may reflect the advantage of no-till in saving fuel costs.

The marginal effect of the *Insured Cropland* variable is significantly negative on the adoption of no-till. This finding provides evidence that farmers purchasing crop insurance are less likely to adopt no-till practices. Since the crop insurance provides partial protection against multi-peril crop losses (including losses from drought or flood), the participants have less incentive to invest in self-protection such as no-till. Given this result, some mechanisms should be added to the current crop insurance program to eliminate or reduce the distorting effects on tillage choices. For example, one mechanism that could be used to reduce this effect is discriminatory pricing for crop insurance, where riskier practices such as conventional tillage require a producer to pay a higher crop insurance premium.

As expected, the time trend variable (T) has a positive and significant effect on the adoption of no-till. The result suggests that technology improvement, assimilation of new knowledge, and policy incentives have increased the adoption of no-till over the years. The negative time-squared (T^2) trend indicates the adoption is increasing at a decreasing rate, providing evidence that agricultural producers are in the latter portion of the no-till technology diffusion curve. Given the fact that no-till is not a new technology, this result is not surprising. However, it does lead us to question how much additional potential there is for the adoption of conservation tillage practices. On the other hand, the adoption of reduced-till is decreasing, and the decreasing rate is slowing down, indicating a switch from reduced-till to alternative practices over time.

Conclusion

Occurrences of weather extremes such as drought, hurricanes, and floods are expected to increase in frequency in the future, because of the impacts of global climate change. The willingness of producers to adapt to these events by adopting risk-reducing practices is of critical importance in understanding the potential economic impacts of climate change.

In this study, we consider one feasible adaptation that reduces the yield risk to agricultural producers—namely, the adoption of alternative tillage systems. Unlike many previous studies which employed cross-sectional data to analyze the choices of tillage systems, we use panel data of pooled cross-sectional and time-series information. The panel data enable us to test

the effects of time-varying factors, including short- and medium-term weather extremes, prices, and policy variables.

We estimate the adoption of three categories of tillage systems relative to conventional tillage: no-till, other conservation tillage, and reduced-till. Results reveal that farmers increase their adoption of conservation tillage following abnormally dry conditions of the past growing seasons; however, abnormally wet conditions (e.g., floods) in the past growing seasons do not have a significant effect on the choice of tillage systems. In addition, we find that excessive rain in the spring poses a critical impediment to the use of no-till. Based on our findings, education programs and technical assistance would be important in helping new adopters overcome difficulties in the early stages of adoption and develop an awareness of the true benefits of practicing no-till.

Another important finding of our study is the significant and negative effect of crop insurance on the adoption of no-till. Farmers whose income is protected by crop insurance have less incentive to invest in self-protection, such as no-till. Likely, we expect a similar effect of other policy variables such as disaster payments, since these payments also provide income protection to farmers. However, the variable of disaster payment is not included in our study due to data limitation—but this is one limitation needing further investigation in our future research.

A better understanding of how farmers adjust their production practices to reduce risks from drought and other hazards is essential for developing effective drought mitigation programs and reducing the impact of other natural disasters. Increasing the resilience to drought through self-protection in the long run should be more cost-effective than smoothing short-term income losses through relief money. The negative effect of crop insurance on the process of self-protection should raise the attention of policy makers when designing the disaster assistance programs.

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