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Ya Ding
University of Nebraska, Lincoln, yding2@unl.edu

Karina Schoengold
University of Nebraska, Lincoln, kschoengold2@unl.edu

Tsegaye Tadesse
University of Nebraska, Lincoln, ttadesse2@unl.edu

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By Ya Ding, Karina Schoengold, and Tsegaye Tadesse

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Ya Ding is a post-doc 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 at the University of Nebraska. Tsegaye Tadesse is a climatologist with the National Drought Mitigation Center at the University of Nebraska. The authors would like to acknowledge the financial support of 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.

Contact information: kschoengold2@unl.edu, 307A Filley Hall, University of Nebraska, Lincoln, NE 68583-0922

Abstract

One benefit of conservation tillage practices is an increase in soil moisture. 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 allows the identification of differences in adoption rates as a function of the severity of past drought or flood events. The adoption of no-till, alternative conservation tillage, and reduced till are estimated relative to conventional tillage. Extremely dry conditions in recent years are found to increase the adoption of both no-till and other conservation tillage practices; while extremely wet conditions (i.e., floods) do not have a significant effect on the choice of tillage practice. In addition, spring floods are found to significantly reduce the use of conservation tillage practices.

Keywords: conservation tillage, drought, technology adoption, weather extremes, panel data

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, 2004). For example, P.L. 108-7 of 2003 provided 3.1 billion dollars 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 dollars 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. 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, 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 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 that 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, the national level 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. 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 that results in increased levels of crop residues in the field. Because no-till conserves soil moisture, its adoption is one strategy that 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 suggested 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 analysis often employed cross-sectional data to analyze 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, 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: 1) we use panel data to account for both cross-sectional and temporal effects; 2) we employ two types of drought index to account for both short-term and mid-term precipitation shocks; 3) we incorporate spatial analysis into the study of tillage choices. The rest of the paper is organized as follows. We first present an analytical model that explains how producer heterogeneity and weather conditions affect the choice of tillage practice. Following that, we develop the empirical model and describe the estimation method. We then explain variables entering the regression model and discuss the estimated results. In the final section, we summarize our findings and give concluding remarks.

Analytical Model

We first consider a standard model of technology adoption, in which a producer chooses a certain type of tillage practice based on his characteristics and expectations about weather during the following season. The model developed is a modification of the irrigation technology choice model used by Caswell and Zilberman (1986). A tillage practice is chosen before planting for a single season, and that choice is reversible in future seasons.

Although we consider several types of tillage practices in the empirical model, for tractability in the analytical model we use two practices, denoted by $i = \{0,1\}$. Practice $i = 0$ is the conventional practice (conventional tillage) and $i = 1$ is the conservation tillage (e.g., no-till or reduced till).

We assume that producers are heterogeneous in characteristics such as land quality and experience. We denote heterogeneity with the parameter θ, where without loss of generality, $\theta \in [0,1]$. A low value of θ means that a producer has poor quality soils, highly erodible land, or other characteristics that limit the productivity of his land. A high value of θ corresponds to high quality soils, low slopes, and other characteristics corresponding with a high productivity of land.

Let the net profit under each tillage practice be denoted by $\pi_i(\theta, w)$, where w is an indicator of weather. We assume that w is a random variable, and that higher values represent weather that is more suitable for crop production. We assume that:

(1) $$\frac{\partial \pi_i(\theta, w)}{\partial \theta} > 0 \quad \forall i$$

(2) $$\frac{\partial \pi_i(\theta, w)}{\partial w} > 0 \quad \forall i$$

(3) $$\frac{\partial \pi_1(\theta, w)}{\partial w} < \frac{\partial \pi_0(\theta, w)}{\partial w} \quad \forall \theta$$

Equation (1) states that a higher value of θ earns a higher profit under all types of tillage practices. Equation (2) states that better weather conditions earn a higher profit under all types of tillage practices. Both of these assumptions make sense for agronomic reasons. Equation (3) states that profit levels under conventional tillage practices are more affected by weather conditions than profit levels with conservation practices. This makes sense for agronomic reasons. Reduced-tillage or no-till practices increase soil moisture, thereby reducing the risk associated with bad weather. Equation (3) is especially important, because it allows us to predict the effect of changes in weather expectations on the adoption of conservation tillage.

In their choice of tillage, producers compare profit levels under the two alternative practices. Let $\Pi(\theta, w) = \pi_1(\theta, w) - \pi_0(\theta, w)$ be the net return of conservation tillage to a producer of type θ, conditional on weather w. If $\Pi(\theta, w) > 0$, the producer will adopt conservation tillage and if $\Pi(\theta, w) < 0$, the producer will use conventional tillage. Using the equations above, we can derive the impact of a change in weather on the choice of tillage practice:

$$(4) \qquad \frac{\partial\left(\Pi(\theta,w)\right)}{\partial w} = \frac{\partial\left(\pi_1(\theta,w)-\pi_0(\theta,w)\right)}{\partial w}$$

$$= \frac{\partial(\pi_1(\theta,w))}{\partial w} - \frac{\partial(\pi_0(\theta,w))}{\partial w} < 0 \ \forall\theta$$

This result shows that the difference in profit levels by tillage practice under optimal weather conditions is lower than the difference in profit levels under poor weather conditions.

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. Mathematically, we assume the following:

$$(5) \qquad \pi_1(0,w) > \pi_0(0,w)$$

$$(6) \qquad \pi_1(1,w) < \pi_0(1,w)$$

Each producer will choose the tillage practice that maximizes his/her profit levels. From Equations (5) and (6), we know that there is a threshold level of $\theta = \bar{\theta}$, where for a single value of w, producers with $\theta < \bar{\theta}$ choose to use conservation tillage and producers with $\theta > \bar{\theta}$ choose to use conventional tillage.

If producers' expectations of weather are constant over time, then producers will choose the tillage practice that maximizes their expected profit. Figure 1 shows this result. Let mean historic weather conditions be denoted by $\bar{w}$, where $E[w] = \bar{w}$. If producers base their expectations of current weather on historic averages, and do not update their expectations of current weather on recent weather events, then we would expect the relative shares of each tillage practice to remain relatively constant over time, conditional on other explanatory variables (e.g., government subsidy programs, increased acceptance and learning about conservation tillage). In the example shown in Figure 1, the critical level of $\bar{\theta}$ that separates those producers using conventional tillage from those using conservation tillage is $\bar{\theta} = \bar{\theta}_{\bar{w}}$.

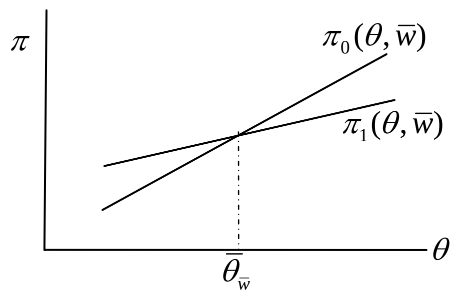

Figure 1: Profits of Alternative Tillage Practices under Mean Weather Conditions

The previous results apply when expectations about weather are constant over time. 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, a producer who endures several years of drought will adjust his/her expectation of weather conditions so that $E[w] = w_L$ instead of $E[w] = \bar{w}$. Figure 2 shows the impact of a change in weather expectation on shares of alternative tillage practices. 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. Therefore, all individuals with $\theta \in [\bar{\theta}_{\bar{w}}, \bar{\theta}_{w_L}]$ will switch from the conventional tillage system to the conservation tillage system.

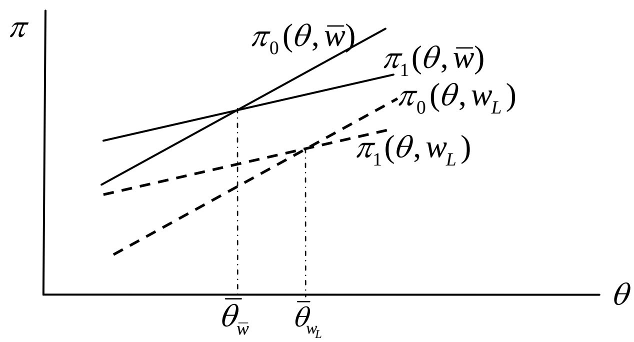

Figure 2: Impact of Changing Weather Expectations on Choice of Tillage Practices

Empirical 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:

$$\begin{aligned} &\Pi = \underset{s^m}{Max}(s^m \pi^m) \\ &s.t. \quad \sum s^m = 1 \end{aligned} \tag{7}$$

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, Tegene, and Wiebe, 2000; Wu and Babcock, 1998; Kurkalova, Kling, and Zhao, 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, weather conditions, site attributes, and other economic variables are used in this study. Solving for the problem in (7), the share of tillage system *m* in county *i* at time *t* can be specified as:

$$s_{it}^{m} = D^{m}(X_{it}) \tag{8}$$

where X_{it} is a vector of explanatory variables including all site specific variables and/or time-varying variables that 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:

$$s_{it}^{m} = \frac{e^{X_{it}\beta^{m}}}{\sum_{m=0}^{M} e^{X_{it}\beta^{m}}} \tag{9}$$

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:

$$\log(s_{it}^{m} / s_{it}^{0}) = X_{it}\beta^{m} + u_{it}^{m} \tag{10}$$

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, like land characteristics; 2) time-series variables, which present little cross-sectional variation, such as prices; 3) cross-sectional and time-series data, such as cropping patterns and weather extremes.

The model specified in equation (5) 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 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. For an introduction to the spatial models, see Anselin (1988). 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. In this study, we extend Zellner's SUR technique to the spatial panel model. The following 3-step procedure is proposed here 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, p195-197). Equation (5) is rewritten as

$$(11) \qquad y_{ti}^{m} = X_{ti}\beta^{m} + u_{ti}^{m} \quad i = 1,...,N;\ t = 1,...,T;\ m = 1,2,3$$

where, $y_{ti}^{m} = \log(s_{ti}^{m} / s_{ti}^{0})$ is the observation of m^{th} tillage system in county i at time t; and u_{ti}^{m} is the error term. Equation (12) shows how we incorporate random effects into the error term, and Equation 13 extends the random effects model to include spatial error autocorrelation.

(12) $u_t^m = \mu^m + \varepsilon_t^m$

(13) $\varepsilon_t^m = \lambda^m W \varepsilon_t^m + v_t^m \quad \rightarrow \quad \varepsilon_t^m = (I_N - \lambda^m W)^{-1} v_t^m = B^{-1} v_t^m$

where $\mu^m = (\mu_1^m, ..., \mu_N^m)'$ denotes the vector of random individual effects, and $\mu_i^m \sim iid(0, \sigma_u^{m\,2})$. W is the NxN weight matrix representing the spatial relationship across counties and λ^m is the corresponding spatial autocorrelation coefficient for equation *m*. Here, *W* is defined as a symmetric contiguous matrix, where each element {wij} equals 1 if county *i* is adjacent to county *j*, and 0 otherwise. $v_t^m = (v_{ti}^m, ..., v_{tN}^m)$, where $v_{ti}^m \sim iid(0, \sigma_v^{m\,2})$ and independent of the μ_i^m. I_N is a NxN identity matrix.

Equation (11) can be rewritten in matrix form as

(14) $Y^{\mathrm{m}} = X\beta^{\mathrm{m}} + u^m \quad with \quad u^m = (l_T \otimes I_N)\mu^m + (I_T \otimes B^{-1})v^m$

where l_T is a Tx1 vector of 1's, and I_T is a TxT identity matrix. The variance-covariance matrix of u^m is

(15) $\Omega^m = E(u^m u^{m\,\prime}) = \sigma_\mu^{m2}(l_T l_T' \otimes I_N) + \sigma_v^{m2}(I_T \otimes (B'B)^{-1})$

The estimation of equation (14) 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[1],

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

(16) $Y^m * = X^m * \beta + e^m \quad m = 1, 2, 3$

where $Y^m *$ and $X^m *$ are the transformed dependent and explanatory variables; and the transformed error term $e^m \sim iid(0, \sigma^{m\,2})$.

Finally, we apply the standard SUR techniques to the system of equations specified in (16) to correct for contemporaneous correlation across equation errors. The 3-step estimation procedure is implemented using MATLAB. The estimated results are presented in Table 4 and 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 3 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. Therefore, these three states make a good study region to analyze the effect of weather extremes on the adoption of no-till. Because of dataset 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 choose to include those counties with at least 60 percent of the land area cultivated.[2] The variables selected for analysis and their

[2] We ran the same analysis for various threshold levels, and the general significance and size of the

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).[3] By the most commonly used definition, conservation tillage is referred to as 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 (less than 15 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 other conservation till. Thus, four categories of tillage systems are analyzed in the empirical model. We chose conventional till as the base category; therefore, 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 hypothesis. Some previously identified factors are not included into the explanatory function for two reasons. First, for some variables like farm size and land tenure, whose values change over the years, county-level data are not available for each year. Second,

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results are unchanged.

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

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 is obtained from USDA/NRCS SSURGO Soils Database. To provide a consistent comparison across counties of varying sizes, we use the percentage of crop land that is 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.[4] However, some researchers suggest 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 not clear. In this study, we use the 30-year (1970-2000) average temperature of February through April to measure the effect of spring temperature on tillage adoption.

Time-series variables

Fuel prices: 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 DOE/EIA.[5]

Time trend variables: A time trend and a squared time trend 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 inter-temporal variables in the explanatory function. With the development of machinery, equipment and management skills suitable for no-till practices, we expect the

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[4] 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).

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

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 4. If we denote the technology adoption rate by A, Figure 4 shows that there is a time $\hat{t}$, where for $t < \hat{t}, \frac{\partial^2 A}{\partial t^2} > 0$; and for $t > \hat{t}, \frac{\partial^2 A}{\partial t^2} < 0$. 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 soybean: The data suggests that conservation tillage is more frequently adopted with the production of corn and soybeans. One explanation that has been suggested is that no-till provides greater benefits with corn and soybeans than with other crops. First, corn and soybean 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 (RMA), approximately 60 percent 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 percent of acres insured in each county as an explanatory variable to determine its effect on the adoption decision of alternative tillage methods.

Weather extremes: As mentioned before, 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 might be also an influencing factor for producers. In this study we construct the weather extreme variables using two types of drought indices: Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI).

(1) PDSI: 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 that 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. On the other hand, rain is the largest 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 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 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 choose 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 anytime before planting in early spring, farmers generally choose their tillage practice immediately after harvest.

The PDSI data are 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 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 classification, PDSI values below -2 indicate moderate drought, and PDSI values greater than 2 indicate moderately wet conditions. However, Wells, Goddard, and Hayes (2004) indicated that the actual values of the historical PDSI values distribution do not fit the normal distribution centered with zero mean. Our PDSI data in the study area have also showed 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 PDSI is below -1.5, the year is defined as a dry year; if 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.

(2) SPI: The SPI is also a widely used drought index in 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 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. Anecdotal evidences suggest that some farmers blamed the compaction problems on no-till, and eventually gave up no-till practices. Therefore, we expect that an abnormally wet spring would reduce the adoption rate of no-till. The April 3-month SPI is used to measure the precipitation anomalies during the springtime. The SPI data for each weather station within the study area are obtained from the High Plains Regional Climate Center (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 zero.

Estimation Results and Discussion

The results show that most of the tested variables have the expected signs, although some are not statistically significant. In the no-till share equation, eight of the thirteen variables display statistically significant influences; six variables are significant in the other conservation-till share equation; and only three variables are significant in the reduced-till share equation. This result implies that the adoption of reduced tillage is probably not distinct from conventional till, and that reduced till may be practiced as a transition between the adoption of conventional till and no-till. 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 estimated coefficients, the marginal effects of explanatory variables are also calculated and reported in Table 5. Notice that the signs of marginal effects are not always consistent with the signs of estimated coefficients.

Cross-sectional variables

The highly erodible land (HEL) has positive coefficients in all three equations but is only significant in the no-till equation. This result makes sense, as the benefits of no-till are greater on poor quality land than on very productive land. The coefficient of 30-year average annual precipitation has the expected sign, but is insignificant in the no-till equation. The coefficients of the average spring temperature are not significantly different from zero in any of the share equations. These results are consistent with previous findings (Rahm and Huffman, 1984; Soule, Tegene and Wiebe, 2000). 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.

Time-series variables

Surprisingly, the coefficients on fuel price have unexpected signs in both the other conservation-till and reduced-till equations. Although it is positive in the no-till equation, it does not show significance. There are a couple of possible explanations. The first is that the annual average motor gasoline price we use in the empirical model does not reflect farmers' actual fuel costs. Another reasonable explanation is that our data covers a period with little variation in fuel prices. There has been a more dramatic increase in fuel prices since 2004, and we expect that with current data, we would find a more significant impact of the fuel price on tillage practices.

As expected, the time trend variable has positive and significant effect in both the no-till and other conservation-till equations. The result suggests that technology improvement, assimilation of new knowledge, and policy incentives have increased the adoption of conservation tillage systems over the year. The negative time-squared trend indicates that 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 conservation tillage 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.

Cross-sectional and time-series variables

The percent of land planted to corn and soybeans has a positive and significant coefficient in all three equations. This result is consistent with our expectation. The marginal effects show that an increase of one percent in the share of corn/soybean land increases the adoption rate of no-till and other conservation tillage practices by 6.0 percent and 23.2 percent, respectively. The same change decreases reduced-till 5.4 percent.

The coefficients on PDSI_dry are positive and significant in both the no-till and other conservation-till equations. The results confirm our hypothesis that farmers experiencing drought in the recent past are more likely to adopt no-till or other conservation tillage systems. Based on the marginal effects, an additional dry year in the previous five years increases the adoption rate of no-till and other conservation tillage practices by about 0.9 and 2.3 percent, respectively. Although the coefficients on PDSI_wet are also positive in the no-till and other conservation-till equations, they are not statistically different from zero. From this we conclude that recent floods have less influence than the recent droughts on farmers' choices of tillage practices.

The coefficients on SPI_wet are negative and significant in both the no-till and other conservation-till equations, which confirms our expectation that a very wet spring poses a serious obstacle to the use of conservation tillage. Although we assume that 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. The marginal effects show that a very wet spring decreases the adoption rate of no-till by 5.1 percent and other conservation-till by 2.7 percent. Conservation tillage must be practiced continuously for several years to 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 stage of practicing conservation tillage.

The coefficient on the crop insurance program variable is significant and negative in the no-till equation. 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.

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.

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 no-till and other conservation tillage in abnormally dry conditions, but that abnormally wet conditions (i.e., floods) do not have a significant effect on tillage practices.

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; fewer efforts are 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: Description of Variables and Summary Statistics

Variables	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 through April	34.817	4.075
Corn-soybean percent	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 ($/million BTU in 2000 dollars)	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
T2	Squared time trend variable	81.667	76.388

Table 2: PDSI 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: SPI Classifications

2.0 or more	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
-2.0 or less	extremely dry

Source: National Drought Mitigation Center

Table 4: Estimated Results

Variables	No-till		Other conservation tillage		Reduced tillage	
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 percent	**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)
T2	**-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)

* T-statistics in parentheses; critical values of t are 2.576, 1.960 and 1.645 at 1%, 5% and 10% level and are denoted by ***, **, and *, respectively.

Table 5: Marginal Effects of Explanatory Variables

Variable	No-till	Other conservation tillage	Reduced tillage
PDSI_DRY	0.009	0.023	-0.017
PDSI_WET	0.009	0.008	-0.011
SPI_WET	-0.051	-0.027	0.017
Precipitation	0.002	-0.005	-0.003
Temperature	0.001	0.004	-0.003
Corn-soybean percent	0.060	0.232	-0.054
Highly erodible land	0.341	-0.117	-0.072
Fuel price	0.015	-0.003	-0.017
Insured cropland	-0.158	0.013	0.063
T	0.120	-0.003	-0.058
T2	-0.005	0.000	0.003

Figure 3: No-till acreage by state

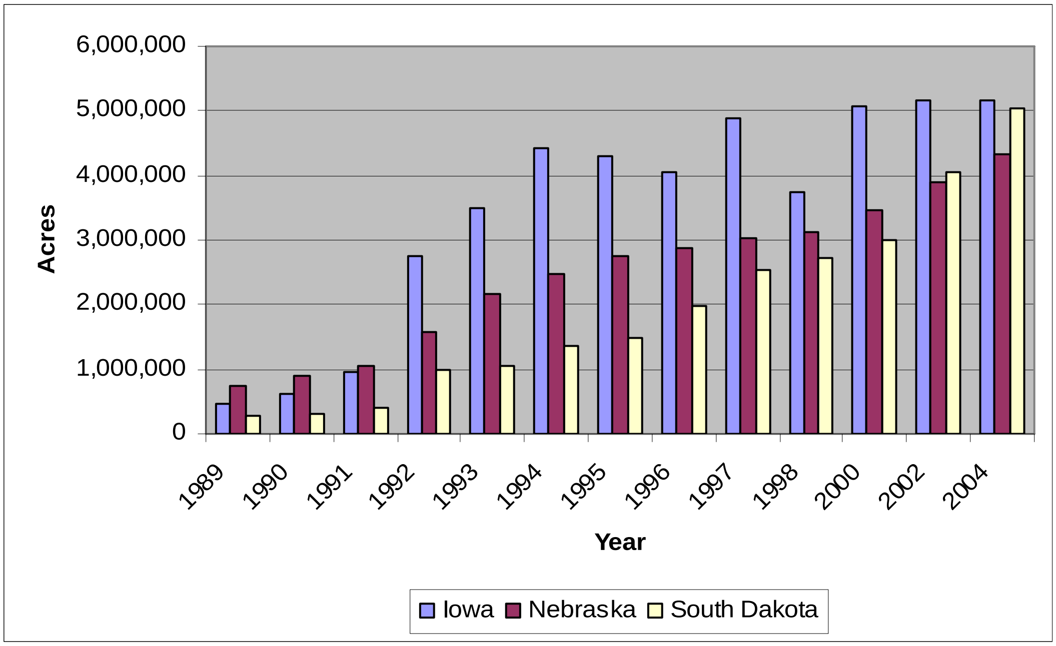

Figure 4: Technology Adoption Rate over Time