Journal of Agricultural and Resource Economics 41(2):266–285 ISSN 1068-5502

Modeling Field-Level Conservation Tillage Adoption with Aggregate Choice Data

Tara Wade, Lyubov Kurkalova, and Silvia Secchi

This empirical study of conservation tillage adoption relies on the logit model applied to field-level information on agents' attributes and county-aggregated measures of agents' choices. The methodology treats the aggregated data as an expected value—the area-weighted group average of individual probabilities of choosing conservation tillage—subject to a measurement error. Using 2002 and 2004 data for Iowa, we estimate field-level costs of the adoption of conservation tillage. The results indicate that adoption is significantly affected by soil characteristics and crop rotation and highlight the heterogeneity in adoption costs when controlling for these characteristics.

Key words: aggregated data, conservation tillage, estimated subsidies, logit model

Introduction

Conservation tillage (CT) is defined as any tillage system that leaves at least 30% of crop residue on the soil surface at the time of planting. CT improves soil structure, reduces soil temperature and evaporation, increases infiltration, and reduces soil erosion and nutrient runoff (Karlen et al., 2009). CT also contributes to soil organic matter and nutrient availability, water retention, macro-invertebrate activity, and carbon sequestration (Horowitz, Ebel, and Ueda, 2010; Center for Agricultural Science and Technology, 2011). Since the benefits of CT accrue to the farmer as well as to society, the practice is recognized as a potent soil and water conservation tool in conservation policy. Climate change mitigation and bioenergy policies are creating a renewed demand for CT use data and models to help understand the environmental footprint of land reverting to cropping from the Conservation Reserve Program and as crop rotations change (Secchi et al., 2011; Center for Agricultural Science and Technology, 2012).

CT also has potential as a climate change mitigation strategy by awarding farmers offset credits that may be sold to point-source emitters of greenhouse gasses (Horowitz, Ebel, and Ueda, 2010). The majority of current conservation programs, such as the Environmental Quality Incentives Program (EQIP), follow an alternative route by providing financial assistance payments to farmers who voluntarily adopt conservation practices (U.S. Department of Agriculture, National Resources Conservation Service, 2012). In either case, to successfully design and implement realistic, cost-minimizing conservation programs, there is a need for both location-specific data on the use of CT and models of farmer- and location-specific tillage adoption (Claassen, Cattaneo, and Johansson, 2008).

Tara Wade is a postdoctoral research associate in the Department of Economics at North Carolina A&T State University. Lyubov Kurkalova is a professor in the Department of Economics and the Department of Energy and Environmental Systems at North Carolina A&T State University. Silvia Secchi is an associate professor in the Department of Geography and Environmental Resources at Southern Illinois University.
We are grateful to anonymous referees who provided valuable feedback. This research was partially funded by the U.S. Department of Agriculture Economic Research Service under cooperative agreements 58–6000–4–0013 and 58–6000–0–0056. The funding source has no involvement in the study design, data collection and analysis, or any other aspects of the research or paper publication. The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the U.S. Department of Agriculture.

Review coordinated by David K. Lambert.

Despite significant data collection efforts and research, the two interrelated tasks—attaining spatially explicit CT data and developing models of CT costs—remain challenging. Data unavailability remains a significant obstacle for empirical CT costs estimation. Though spatially detailed Geographic Information Systems (GIS) data on cropping patterns and soil properties are becoming increasingly accessible (Stern, Doraiswamy, and Akhmedov, 2008; Secchi et al., 2009, 2011; Khanna et al., 2011; Archer and Johnson, 2012), CT use data are rarely available at the same spatial scale. Aerial photography-based CT data methodologies are developing, but their accuracy is still low over large geographic areas (Thoma, Gupta, and Bauer, 2004; Bricklemyer et al., 2006; Zheng et al., 2013). The commonly used Conservation Technology Information Center (CTIC) National Crop Residue Management Survey (NCRMS) tillage data (Conservation Technology Information Center, 2012a,b) are only available as aggregated, county-total estimates. A noteworthy recent data collection effort is Conservation Effects Assessment Project (CEAP) within the National Resources Inventory (NRI) (U.S. Department of Agriculture, National Resources Conservation Service, 2012). However, because of confidentiality restrictions, the results of the CEAP-NRI studies are only available as aggregated totals over large watersheds that span across multiple states (U.S. Department of Agriculture, National Resources Conservation Service, 2012). The other notable source of U.S. CT use estimates is the U.S. Department of Agriculture's Agricultural and Resource Management Survey (ARMS) (Horowitz, Ebel, and Ueda, 2010). However, data collection budgets limit the periodicity and sample size of ARMS, and confidentiality concerns frequently result in the availability of the survey results in county- or state-total form only (Banerjee et al., 2009; Smith, 2013). In effect, only spatially aggregated data are readily available for public use.

While spatially aggregated CT use data are useful for assessing farmers' choices at the macro scale, to capture marginal rather than average effects, microeconomic analysis requires spatially disaggregated data to account for the heterogeneity in land resources, climate, farm organization, and farmers' characteristics (Just, 2000; Lambert et al., 2007). The profitability of CT relative to conventional tillage varies across space and farms and depends on crops grown, soil properties, and climatic conditions (Horowitz, Ebel, and Ueda, 2010). Few empirical studies have developed estimates of location- and farmer-specific costs of CT adoption based on observed farmers' choices (Cooper, 1997; Lichtenberg, 2004). The models developed by Pautsch et al. (2001), Wu et al. (2004), and Kurkalova, Kling, and Zhao (2006) were estimated on data from 1992 or earlier, and more empirical research is needed to better reflect changes in production technologies and economic environment.

Two approaches to overcoming the mismatch between the field-scale cropping and soils data and more spatially aggregated CT use data have emerged in the recent literature. One involves the use of budget analysis on the GIS-based crops and soils data to simulate the profit-maximizing choice of tillage (Secchi et al., 2009, 2011; Khanna et al., 2011; Archer and Johnson, 2012). Our study draws on the second approach, which applies econometric models consistent with underlying economic behavior to combined spatially aggregated tillage use data and spatially disaggregated data on the determinants of tillage choices to estimate field-level discrete choice models of CT (Kurkalova and Rabotyagov, 2006; Kurkalova and Wade, 2013). This approach allows the use of readily available CTIC tillage data and GIS-based land use and soil data to estimate spatially detailed costs.

This study contributes to the literature by assessing how the costs of CT adoption vary spatially with soil and landscape properties and by crop rotation. This is achieved through application of a recently developed Group Dependent Variable Logistic (GDVL) model (Kurkalova and Wade, 2013) to CTIC 2002 and 2004 Iowa data to estimate field-level costs of CT adoption. The GDVL model treats the aggregated data as an expected value—the crop and county area-weighted average of individual probabilities of choosing CT subject to a normal measurement error—and uses the maximum likelihood method to estimate the parameters of a logistic, field-level model of CT choice. It also quantifies the variation in the normal and logistic errors. To our knowledge, the cost estimates we obtain are the most recent available and the only ones linked to GIS-based crop cover and soils data.

Economic Model of Conservation Tillage Adoption

The modeling approach follows Kurkalova, Kling, and Zhao (2006) and assumes that a farmer will adopt CT when the expected net returns from this practice exceed those from conventional tillage plus an adoption premium. Farmers may require a premium to adopt CT because of the uncertainty in the CT returns and attitudes toward risk (Kurkalova, Kling, and Zhao, 2006; Cooper and Signorello, 2008). The expected net returns from conventional tillage, NR, are assumed known to both researchers and farmers, while the expected net returns to CT and the premium are assumed known to farmers but unknown to researchers. Let Y be the observable binary variable representing the adoption of CT (i.e., $Y = 1$ if a farmer uses CT on his/her field, and 0 otherwise). From the researchers' perspective, the probability of CT adoption is written as

$$\Pr(Y=1) = \Pr(\sigma_\eta \eta \leq \boldsymbol{\alpha}'\boldsymbol{w} - \boldsymbol{\gamma}'\boldsymbol{z} - NR), \tag{1}$$

where $\boldsymbol{\alpha}'\boldsymbol{w}$ represents the expected net returns to CT as a function of the unknown vector of parameters, $\boldsymbol{\alpha}$, and the observed vector of explanatory variables, $\boldsymbol{w}$; $\boldsymbol{\gamma}'\boldsymbol{z}$ represents the premium as a function of the unknown vector of parameters, $\boldsymbol{\gamma}$, and the observed vector of explanatory variables, $\boldsymbol{z}$; η is a logistic error reflecting the researchers' ignorance about the exact relationship between the expected net returns to CT and the premium and the corresponding explanatory variables; and σ_η is the unknown standard deviation multiplier. Since the data on NR are available, all the parameters of equation (1) are identifiable (Kurkalova, Kling, and Zhao, 2006). If the farmer has already adopted CT, then the expected net returns from CT are greater than or equal to those from conventional tillage plus the premium, and the cost of CT adoption is equal to zero. If the farmer is using conventional tillage, then the cost of CT adoption must be positive. Once the model parameters are estimated, the cost of CT adoption, S, which is also the minimum subsidy needed to induce CT adoption for present nonadopters, can be predicted as the difference between the expected net returns to conventional and conservation tillage, plus the premium:

$$S = \max(NR - \hat{\boldsymbol{\alpha}}'\boldsymbol{w} + \hat{\boldsymbol{\gamma}}'\boldsymbol{z}, 0), \tag{2}$$

where a "hat" indicates the estimated value of the parameter.

To simplify the notation, denote

$$\boldsymbol{\beta}' = \left(\frac{1}{\sigma_\eta}\boldsymbol{\alpha}', \; -\frac{1}{\sigma_\eta}\boldsymbol{\gamma}', \; -\frac{1}{\sigma_\eta} \right), \; \boldsymbol{x} = \begin{pmatrix} \boldsymbol{w} \\ \boldsymbol{z} \\ NR \end{pmatrix}. \tag{3}$$

Then equation (1) could be written as a standard binary choice model:

$$\Pr(Y=1) = \Pr(\eta \leq \boldsymbol{\beta}'\boldsymbol{x}). \tag{4}$$

If a sample of field-level data on both the adoption of CT, Y, and the explanatory variables, $\boldsymbol{x}$, is available, equation (4) parameters, $\boldsymbol{\beta}$, are estimable using the standard logit model techniques. However, the individual choices, Y, are unavailable in the data, making the standard logit impossible to estimate. This data structure is often observed by agri-environmental researchers. The next section presents a modification of equation (1) that permits identification of the parameters of interest when only aggregated data on dependent variables are observable.

Maximum Likelihood Estimation of the Grouped Dependent Variable Logistic Model

Consider a sample of N fields indexed by i, each a_i acres, for which a farmer makes an independent tillage decision. Let $Y_i = 1$ if CT is used on the field and $Y_i = 0$ if conventional tillage is used, and let the choice of CT for each field be governed by equation (4). The GDVL model (Kurkalova and Wade, 2013) assumes that researchers know the individual acres farmed, a_i, but do not observe field-level CT choices, Y_i. Instead, the sample is divided into J distinct groups, G_j, indexed by j, each containing N_j fields, so that $\sum_{i \in G_j} i = N_j$, $\sum_{j=1}^{J} N_j = N$, where researchers observe the estimates of the shares of acres in CT for each group j. The estimates of the shares of acres in CT for each group are assumed to be the acres-weighted expected values of the group-averaged individual choice variables, $\frac{1}{\sum_{i \in G_j} a_i} \sum_{i \in G_j} a_i Y_i$, subject to the normal errors, with the latter distributed identically and independently across the groups. That is,

$$(5) \qquad p_j = \frac{1}{\sum_{i \in G_j} a_i} \sum_{i \in G_j} \frac{a_i \exp(\boldsymbol{\beta}' \boldsymbol{X}_i)}{1 + \exp(\boldsymbol{\beta}' \boldsymbol{x}_i)} + \varepsilon_j, \ \varepsilon_j \sim N(0, \sigma_\varepsilon),$$

where p_j is the observed share of acres in CT in group j, $\boldsymbol{x}_i$ is the observed vector of explanatory variables corresponding to field i, ε_j is the error representing the uncertainty about the estimate of the group j-average use of CT, and σ_ε is an unknown parameter.

The probability equation (5) leads to the following likelihood for the jth group of observations:

$$(6) \qquad L(\boldsymbol{\beta}, \sigma_\varepsilon | p_j, \boldsymbol{x}_i(i \in G_j)) = -\frac{1}{2} \ln(2\pi\sigma_\varepsilon^2) - \frac{1}{2\sigma_\varepsilon^2} \left\{ p_j - \frac{1}{\sum_{i \in G_j} a_i} \sum_{i \in G_j} \frac{a_i \exp(\boldsymbol{\beta}' \boldsymbol{x}_i)}{1 + \exp(\boldsymbol{\beta}' \boldsymbol{x}_i)} \right\}^2 .$$

To estimate the parameters of interest, $\boldsymbol{\beta}$ and σ_ε, we apply the method of maximum likelihood based on equation (6) to the data described in the next section.

Data Description and Variable Construction

The empirical study of Iowa's corn and soybean production combines (1) CT use data from the CTIC NCRMS (Conservation Technology Information Center, 2012a); (2) cropping pattern data from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) remote sensing Cropland Data Layers (U.S. Department of Agriculture, National Agricultural Statistics Service, 2010); (3) soils data from Iowa's Soil Properties and Interpretations Database 7.0 (ISPAID) (Iowa State University, 2004); (4) climatic data from the National Climatic Data Center (National Climatic Data Center, 2010); and (5) farm indicators from the 2002 Census of Agriculture (U.S. Department of Agriculture, National Agricultural Statistical Service, 2004). Table 1 provides the descriptive statistics of the dependent and independent variables.

Dependent Variable/ Tillage Adoption

We opt to investigate the costs of CT rather than a single tillage system (e.g., no-till) because disparate CT practices often have similar suites of benefits. Combining the acres used under multiple practices gives a better understanding of the costs associated with improving environmental benefits. The NCRMS is the only consistent national survey of county-average CT use, which ran annually from 1989 to 1998 and biannually from 1998 to 2004.[1] We use the two latest years of Iowa data available, 2002 and 2004, and focus on corn and soybeans, since they occupied the overwhelming majority of Iowa cropland in 2002 and 2004, (92% and 94%, respectively) (U.S. Department of Agriculture, National Agricultural Statistics Service, 2013). The CTIC records are based on the roadside transect method: county conservation experts drive a set course to visually assess CT use at half-mile or mile intervals (Conservation Technology Information Center, 2012b). Any field with

[1] Other recent data on the use of CT were reported at even higher levels of aggregation such as a state (Horowitz, Ebel, and Ueda, 2010) or a multi-state (large watershed) (U.S. Department of Agriculture, National Resources Conservation Service, 2012).

Table 1. Variable Descriptions and Summary Statistics

Name	Description	Units	Mean	Standard Deviation
p	County average proportion of corn or soybean acres in conservation tillage	Number	0.59	0.26
I_C	Indicator for corn, i.e., 1 if the crop is corn and 0 otherwise	Number	0.54	0.50
I_S	Indicator for soybeans, i.e., 1 if the crop is soybeans and 0 otherwise	Number	0.47	0.50
I_{CS}	Indicator for corn following soybeans rotation, i.e., 1 if the crop is corn and previous crop is soybeans and 0 otherwise	Number	0.31	0.46
a	Acres in the field	100 acres	3.0	8.9
NR	Expected net returns to conventional tillage	\$100/acre	1.1	1.0
$SLOPE$	Land slope	Percentage	5.0	5.1
$PERM$	Soil permeability	Number	50	17
$FLOOD$	Flood frequency	Number	5.0	12
$PRCP$	Mean of daily precipitation during the corn growing season	Inches	0.1240	0.0086
$TMAX$	Mean of daily maximum temperature during the corn growing season	Fahrenheit	77.9	1.5
σ^2_{prcp}	Variance of daily precipitation during the corn growing season	Inches^2	0.133	0.017
EXP	County average of farm operators' years on the present farms	Years	24.0	1.2
$MALE$	Proportion of male operators to the total number of farm operators in the county	Number	0.932	0.026
$CORP$	Proportion of farms operating as family-held corporations to the total county farms	Number	0.058	0.025

30% or more of crop residue after planting is considered as CT. We use the county proportion of CT acres relative to the total acres for each crop, corn and soybeans, as the dependent variable, $p_j,\ j = 1, \ldots, J$. Here $J = 396$ (99 counties $\times$ 2 crops $\times$ 2 years).

Independent Variables

Following the literature on CT adoption, the independent variables include crop and previous crop, soil and landscape characteristics, weather and climatic variables, and farm and farmer characteristics (Kurkalova, Kling, and Zhao, 2006; Knowler and Bradshaw, 2007; Prokopy et al., 2008; Lichtenberg et al., 2010).

Combining Data from Different Sources

The cropping patterns and soil characteristics data are at the field level. The indicators of the current and previous years' crops grown come from the 2001, 2002, 2003, and 2004 Cropland Data Layer (U.S. Department of Agriculture, National Agricultural Statistics Service, 2010). The original sample consists of corn and soybean areas totaling 21.1 million acres for 2002 and 22.2 million acres for 2004. The cropping sequences (rotations) for each field were identified by overlaying the 2002 map with 2001 maps and 2004 maps with 2003 maps. Because we observe cross-sections of data for 2002 and 2004 and field shapes and sizes may change over time, the data do not form a panel.

The three crop-previous crop combinations considered—corn following corn (CC), corn following soybeans (CS), and soybeans following corn (SC)—cover the overwhelming majority of Iowa cropland (Stern, Doraiswamy, and Akhmedov, 2008; Horowitz, Ebel, and Ueda, 2010). In the case of soybeans, an unusual 7% of the original remote sensing Cropland Data Layer indicate soybeans following soybeans. Due to problems with *Heterodera glycines* (Workneh et al., 1999), pod rot, and sudden death (Baird et al., 1997)—among other diseases associated with this rotation, as well as the significant yield decline associated with consecutive years of soybeans (Hennessy, 2006)—soybeans after soybeans is an unlikely choice for Iowa farmers seeking to maximize profits.[2] Because of these considerations and following the previous uses of Iowa Cropland Data Layer data (Kurkalova, Secchi, and Gassman, 2010; Secchi et al., 2009), fields that show soybeans following soybeans are reassigned to SC. Overall, 13.5% of the available corn and soybeans field-level data were excluded from the study because the previous year land cover was classified as a crop other than corn or soybeans, pasture, forest, water, or because clouds precluded identification of the land use data.

A GIS program (ArcView) was used to link the field-level crop and previous crop data with the soil properties data from ISPAID and with information from the 162 weather stations with complete information for climatic variables from National Climatic Data Center. A GIS script was used to construct the Thiessen polygons around the weather stations to partition the state's cropland. The polygons' boundaries define the areas closest to each weather station, so each field is assigned a polygon and a weather station. [3]

Because the original resolution of the Cropland Data Layer GIS data was 30m by 30m, the overlay of multiple years of land use, the Thiessen polygons with the weather information, and the soils data produced an unmanageable dataset for the GIS program. To keep the data manageable, the Thiessen polygons were rasterized (i.e., converted from vector to pixel image structure) at a 400m by 400m resolution (approximately 37.4 acres); the soil database was then combined with the Thiessen polygon layer. The resulting dataset was then combined with the 2001 and 2002 land use, and then with the 2003 and 2004 layers to create the two cross-sectional datasets used in the analysis.

The final two-year sample has $N = 123,157$ observations, of which 15% are in CC, 39% in CS, and 46% in SC. The median number of fields per group (N_j) is 333, with the smallest group having 85 fields and the largest having 760 fields. The average field size in the sample, a_i, is 303 acres. The pooled sample represents 37.4 million acres. In comparison, USDA/NASS reports that corn and soybeans in Iowa were harvested on 22,250,000 acres in 2002 and on 22,550,000 acres in 2004. Thus, our data covers approximately 83% of the state's land cropped in corn and soybeans.

Cropping Patterns

To quantify the effect of both crops (corn versus soybeans) and cropping sequences (CS versus CC) on the adoption of CT, we use three indicator variables: I_C, coded as one if the crop is corn and zero otherwise; I_S, coded as one if the crop is soybeans and zero otherwise; and I_{CS}, coded as one if the crop-previous crop combination is CS and zero otherwise (table 1). *Ceteris paribus*, we expect the probability of CT adoption to be higher and, consequently, the cost of the adoption of CT to be lower, on soybean versus corn fields. The reason is that there is evidence in controlled agronomic experiments that tillage has little effect on soybean yields and no-till is commonly seen on soybeans (Horowitz, Ebel, and Ueda, 2010). The CTIC sample itself reports the adoption rate of soybeans to be almost twice that of corn (table 2).

On corn fields, *ceteris paribus*, we expect the probability of CT adoption to be higher and, consequently, the costs of CT adoption to be lower, on rotated (i.e., CS) versus nonrotated (i.e., CC) fields, since rotating crops helps with weed management and thus reduces the need to till (Shaw et al., 2012). However, few economic studies have assessed the impact of rotations on CT adoption. Although Fuglie (1999) found that crop rotation has an insignificant effect on CT adoption, the results of Wu and Babcock (1998) and De La Torre Ugarte, Hellwinckel, and Larson (2004) imply that rotating crops positively affects CT use.

---

[2] We acknowledge that there may be few farmers in the sample that may have planted soybeans following soybeans for a limited number of factors beyond the farmers' control (e.g., machine failures). We opt to include these fields in the study as SC fields since we contend that these farmers are primarily interested in maximizing profits and therefore use continuous soybeans on minimal acreage.

[3] Mathematically, the Thiessen polygons are defined by the perpendicular bisectors of the lines between all points.

Table 2. Sample Acre-Weighted Average Yield and Average Acres

Crop or Rotation	Year	Yield (bu/acre)	Acres (%)	CT Adoption (%)
Corn	2002	165 (42)	55	41 (22)
	2004	185 (42)	53	40 (22)
CC	2002	165 (44)	15	
	2004	181 (45)	15	
CS	2002	166 (41)	40	
	2004	186 (41)	38	
SC	2002	49 (11)	45	71 (19)
	2004	49 (12)	47	81 (15)

Notes: Standard deviations in parentheses.

Net Returns to Conventional Tillage

The data on expected net returns to conventional tillage, *NR*, are vital to estimating the monetary incentives to switch to CT methods as they are used to identify the logistic error multiplier, σ_η (equation 1). Since the model needs a good approximation of individual net returns, these data are calculated using field-level crop yield estimates. While reliable county-level yield data are readily available, the aggregation results in a poor representation of field-level variability (Claassen and Just, 2011). To capture the intra-county heterogeneity in expected yields, we use the Corn Suitability Rating (CSR) available for all Iowa ISPAID soils. The CSR is an index ranging from 0 to 100 with higher values corresponding to better suitability for crop production (Iowa State University, 2004). To develop the county-specific relationship between the CSR and the potential crop yield we follow the procedure of Secchi et al. (2009).[4] Table 2 provides the averages of the estimated field yields by year and crop sequence.

We construct *NR* estimates for each field as the difference between the expected revenue and cost. The field-specific potential yield data were combined with state-level prices in the corresponding years (Johanns, 2011c), and the crop- and previous crop-specific cost estimates were based on the estimation of typical 2002 and 2004 Iowa costs of crop production by Iowa State University Extension (Duffy and Smith, 2002, 2004). These cost estimates are guidelines used by Iowa farmers to anticipate production costs. Since the production input and output prices are assumed homogeneous across the state, the distribution of *NR* is driven by the distribution of the expected yields.

Net Returns to Conservation Tillage and Premium

Following previous analyses, the soil characteristics postulated to affect the net returns to CT (vector $\boldsymbol{w}$ in equation 1) include the land slope, drainage in the form of permeability, and frequency of floods. Cropland is identified as highly erodible land (HEL) if the potential of soil erosion is eight times or more the rate at which the soil can sustain productivity (U.S. Department of Agriculture, National Resource Conservation Service, 2002). Land classified as HEL is often enrolled in conservation programs or is subject to conservation compliance that mandates the use of conservation practices to maintain eligibility for government payments (Giannakas and Kaplan, 2005; Secchi et al., 2009). Therefore, HEL status is expected to positively affect the adoption of CT. This variable is available in the ISPAID database, but some 1,466 observations representing 97,771 acres are not assigned an HEL category. Hence, another widely used variable, land slope, is used as a proxy for HEL (Fuglie and Bosch, 1995; Knowler and Bradshaw, 2007; Sheeder and Lynne, 2011). *SLOPE* here is the average of the lowest and highest range of the incline of the soil surface (Iowa State University,

[4] Details of the calculations for this dataset are available from the authors upon request.

2004). This variable's high collinearity with HEL (correlation coefficient of 0.8) and the retention of the observations make it a favorable choice.

Well-drained soil is important when using CT (Al-Kaisi and Yin, 2004; Yin and Al-Kaisi, 2004; Triplett and Dick, 2008) and soil permeability code, *PERM*, is used to capture this effect. The permeability code ranges from 0 to 90 for high to low permeability. Because of the residue cover on CT land, less permeable soil can potentially get waterlogged. De La Torre Ugarte, Hellwinckel, and Larson (2004) found that incentive payments to fields with well-drained soils are lower than those made to poorly drained soils. *PERM* is therefore predicted to have a negative impact on the probability of CT adoption.

Ding, Schoengold, and Tadesse (2009) estimated that farmers are less likely to use no-till in the years when they experience flooding. The fields may be prone to flooding because of proximity to water bodies, potential heavy precipitation in short periods of time, or landscape and soil features that preclude adequate movement of water through the soil surface during precipitation events. To capture the effect of flooding vulnerability we use the *FLOOD* indicator, which describes how often soil is temporarily covered with water from overflowing streams and runoff from adjacent slopes (Iowa State University, 2004). *FLOOD* is indexed from 0 to 50 (from no flooding to ponded) and is expected to have a negative impact on the probability of CT adoption.

Constructed climate regressors capture both within-season and cross-seasonal variations in temperature and precipitation. The climate data were calculated from the National Climatic Data Center daily precipitation and maximum temperature measurements over the corn growing season for the years 1970–2004 (National Climatic Data Center, 2010). Since the growing season spans from planting to harvesting, the climate regressors are constructed using the temperature and precipitation data ranging from the mid-date in the range of the most active corn planting period (May 10) to the mid-date in the range of the most active corn harvesting period (October 23) (U.S. Department of Agriculture, National Agricultural Statistics Service, 2010).[5]

The econometric model utilizes climate variables in two ways: as contributors to the estimation of the net returns to CT and to model the adoption premium (vectors $\boldsymbol{w}$ and $\boldsymbol{z}$ in equation 1, respectively). The regressors used in the estimation of the net returns to CT are the means of the daily maximum temperature and precipitation (*TMAX* and *PRCP*). Long-run weather variables were used in previous studies with mixed results: Kurkalova, Kling, and Zhao (2006) showed positive and insignificant impact of average precipitation and positive and significant impact of maximum temperature, Ding, Schoengold, and Tadesse (2009) showed negative and insignificant effect of precipitation, and positive insignificant impact of average temperature, Soule, Tegene, and Wiebe (2000) showed a negative effect of precipitation and temperature on the adoption of CT. Despite mixed empirical evidence, the common expectation is that CT does not perform well on cold, wet soil (Soule, Tegene, and Wiebe, 2000). *PRCP* is therefore expected to have a negative effect on the adoption of CT and *TMAX* is expected to have a positive effect.

The variance of daily precipitation, σ^2_{prcp}, is calculated using the daily rainfall totals from the same thirty-five-year period. Following Kurkalova, Kling, and Zhao (2006), we model the adoption premium as a multiplicative function of the variance of precipitation. The adoption premium exists because of the variability of the CT payoff, which in turn is related to the sensitivity of crop yields to weather variability—precipitation in particular.

To model the impact of farm and farmer characteristics, we follow previous research and include farmer's income, experience, gender, and farm organization (Prokopy et al., 2008; Lichtenberg et al., 2010). The only field-level variable in this category, the net returns to conventional tillage, *NR*, is used as a proxy to farmer's income. The rest are county-average statistics from the 2002 Census of Agriculture (2004). The statistics used are the county average of farm operators' years on the present farms, *EXP*, and the proportion of male operators to the total number of farm operators in the county, *MALE*. We also use the county-average proportion of farms operating as family-

[5] There are only ten days between the corn and soybeans growing season, so we opt to use only the corn growing season dates.

Table 3. Model Estimates

Variables	Coefficients, $\boldsymbol{\beta}$	Estimates
I_S	β_1	5.5 (1.7)***
I_{CS}	β_2	2.2 (1.2)*
$SLOPE$	β_3	0.41 (0.12)***
$PERM$	β_4	−0.0255 (0.0086)***
$FLOOD$	β_5	−0.066 (0.025)***
$PRCP$	β_6	−8 (13)
$TMAX$	β_7	0.063 (0.036)*
$NR \cdot \sigma^2_{prcp} \cdot I_C$	β_8	−0.33 (0.10)***
$NR \cdot \sigma^2_{prcp} \cdot I_S$	β_9	−0.38 (0.10)***
$EXP \cdot \sigma^2_{prcp} \cdot I_C$	β_{10}	0.10 (0.58)
$EXP \cdot \sigma^2_{prcp} \cdot I_S$	β_{11}	0.95 (0.57)*
$MALE \cdot \sigma^2_{prcp} \cdot I_C$	β_{12}	42 (19)**
$MALE \cdot \sigma^2_{prcp} \cdot I_S$	β_{13}	42 (19)**
$CORP \cdot \sigma^2_{prcp} \cdot I_C$	β_{14}	−95 (40)**
$CORP \cdot \sigma^2_{prcp} \cdot I_S$	β_{15}	−75 (34)**
NR	β_{16}	0.051 (0.015)***
	σ_ε	0.1700 (0.0060)***
Log Likelihood		139.867

Notes: Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.

held corporations to the total county farms, *CORP*, to test the hypothesis that organization type influences the CT adoption decision. If different types of organizations have differences in types of expenditures, access to loans, or have distinctive types of leasing and tenure arrangements, they may choose different soil management systems or may find it arduous to switch to different mechanisms. As with many other farm and farmer characteristics, the empirical results from previous research yield no consensus. Napier and Tucker (2001) found that organizational structure has no significant effect on predicting conservation behavior. However, Davey and Furtan (2008) suggested a positive effect of family organizations on adoption.

The equation estimated is given by equation (7), where, omitting the subscript i for the sake of simplicity in notation,

$$
\begin{aligned}
\boldsymbol{\beta}'\boldsymbol{x} = \; & \beta_1 \cdot I_S + \beta_2 \cdot I_{CS} + \beta_3 \cdot SLOPE + \beta_4 \cdot PERM + \beta_5 \cdot FLOOD \\
& + \beta_6 \cdot PRCP + \beta_7 \cdot TMAX + \{(\beta_8 \cdot I_C + \beta_9 \cdot I_S) \cdot NR \\
& + (\beta_{10} \cdot I_C + \beta_{11} \cdot I_S) \cdot EXP + (\beta_{12} \cdot I_C + \beta_{13} \cdot I_S) \cdot MALE \\
& + (\beta_{14} \cdot I_C + \beta_{15} \cdot I_S) \cdot CORP\} \cdot \sigma^2_{prcp} + \beta_{16} \cdot NR.
\end{aligned} \tag{7}
$$

In separating the CT choice determinants into those affecting net returns to CT and those affecting the adoption premium, we follow the only studies that have addressed the partition empirically: Kurkalova, Kling, and Zhao (2006) and Kurkalova and Rabotyagov (2006). The first seven terms in equation (7) represent the expected net returns to CT postulated to be a linear function of rotation, soil characteristics, and climatic variables. The adoption premium is modeled as a linear function of farm and farmer characteristics, all interacted with the variability of precipitation and varying by the crop grown. A positive β_i, $i = 1, \ldots, 7$, implies a positive impact of the corresponding explanatory variable on the likelihood of adoption and a negative impact on the cost of CT adoption. The direction of these impacts reverses for the premium terms (i.e., for β_i, $i = 8, \ldots, 15$). As evident from equations (1) and (3), estimation of β_{16} leads to estimation of $\sigma_\eta = -1/\beta_{16}$.

Table 4. Average Relative Error of the Estimated Proportion of Acres in CT

Crop Reporting District	All		Corn		Soybean	
	Estimated Proportion	Relative Error, %	Estimated Proportion	Relative Error, %	Estimated Proportion	Relative Error, %
Northwest	0.574	1.55	0.399	2.92	0.766	0.78
North Central	0.466	3.60	0.286	7.74	0.686	1.63
Northeast	0.522	7.68	0.350	10.01	0.766	6.12
West Central	0.598	3.29	0.466	4.65	0.751	2.33
Central	0.580	10.08	0.423	18.99	0.759	5.09
East Central	0.603	3.12	0.455	0.26	0.809	5.26
Southwest	0.712	2.19	0.632	2.74	0.804	6.24
South Central	0.599	8.32	0.453	16.12	0.741	2.99
Southeast	0.565	5.28	0.397	11.92	0.761	0.71

Results and Discussion

Table 3 displays the results of estimating equation (5) with the specification ($\boldsymbol{\beta}'\boldsymbol{x}$) given in equation (7). The generalized likelihood ratio test of the hypothesis that all the coefficients in equation (7) corresponding to the adoption premium are equal to zero (i.e., $\beta_i = 0,\ i = 8,\ \ldots,\ 15$) was rejected as the computed value of the test statistic, 41.709, is statistically significant at the 1% level. Likewise, the generalized likelihood ratio test rejected, at a 10% level of significance, the specification in which premium terms did not vary by crop (the computed value of test statistic, 7.802, has a p-value of 0.099). The generalized likelihood ratio test did not find the support for the model in which the standard deviation multiplier of the logistic error, σ_η, varies by crop as the computed value of the test statistic, 0.369, has a p-value of 0.544.

To evaluate the overall fit of the model, we compared the observed dependent variable data with the values of the dependent variables predicted as the corresponding expected values conditional on the parameter estimates. The standard measure of logit model fit—the percentage of correct predictions—is not possible to compute because the data on tillage choices are available in the grouped form only. Consequently, we compared the predicted and the observed grouped choices only. Based on equation (5), we predicted the county proportion of the CT acres relative to the total acres for each crop and year as $\hat{p}_j = \frac{1}{\sum_{i\in G_j} a_i}\sum_{i\in G_j}\frac{a_i \exp(\hat{\boldsymbol{\beta}}'\boldsymbol{x}_i)}{1+\exp(\hat{\boldsymbol{\beta}}'\boldsymbol{x}_i)},\ j = 1,\ \ldots,\ 396$, where $\hat{\boldsymbol{\beta}}$ denotes the estimated values of the parameters β. A counterpart of the standard regression coefficient of determination, the share of the explained sum of squares in the total sum of squares, $\sum_j(\hat{p}_j - p_j)^2/\sum_j(\overline{p} - p_j)^2$, where $\overline{p} = \sum_j p_j/396$, is estimated as 0.433. We also evaluated the relative errors of prediction, $|\hat{p}_j - p_j|/p_j \cdot 100\%$ for each group $j,\ j = 1,\ \ldots,\ 396$.[6] Table 4 displays the acre-weighted average of the relative errors of prediction for each crop-reporting district.[7] A crop-reporting district is a multiple county unit within a state, the boundaries of which are determined by USDA/NASS (U.S. Department of Agriculture, Economic Research Service, 2000).

One unique feature of the GDVL method is the ability to quantify the deviations in both the logistic error, η, attributable to the standard logistic model, and the normal error, ε, attributable to the aggregation of the binary choice data. We find both $\sigma_\eta = 19.5$ and $\sigma_\varepsilon = 0.17$ to be statistically significant at a 1% level of significance. Because of the different datasets used, the estimated σ_η is not directly comparable to the estimates obtained in previous studies. The normal error reflects the inaccuracy of the CTIC data, which has not been quantitatively evaluated.[8]

---

[6] This model fit evaluation approach is similar to that used by Skaggs, Kirksey, and Harper (1994).

[7] Since Iowa has ninety-nine counties, the estimates by county are impractical to display here. For a map of Iowa crop reporting districts see, for example, U.S. Department of Agriculture, Economic Research Service (2000).

[8] Thoma, Gupta, and Bauer (2004) estimate CTIC data accuracy at approximately 74% using ground proofing methods for Minnesota corn and soybean fields in 1999. The potential errors of the CTIC data are also discussed in Baker (2011).

Determinants of Conservation Tillage Adoption

As expected from the relatively common adoption of no-till on soybeans, we estimate a positive impact of I_S on the adoption of CT. The statistically significant, positive impact of I_{CS}, relative to CC is consistent with the agronomic studies and points to the higher implied costs of CT adoption under nonrotated versus rotated corn. The importance of improved understanding of the relationship between corn monoculture and tillage choices is growing, as the biofuels boom is generating larger than historically average corn acreages with the share of CC increasing (Secchi et al., 2011; Center for Agricultural Science and Technology, 2012).

In keeping with the consensus that CT does not operate well under damp conditions, we estimate the impacts of $PERM$ and $TMAX$ as expected with regards to the direction of the effect, which is statistically significant. The effect of precipitation, $PRCP$, is likewise of the expected sign, though statistically insignificant. The positive and significant effect of $SLOPE$ is consistent with highly sloped fields being placed in conservation programs. Similar effects of the soil and climatic factors have been estimated before (see, for example, the discussions in Kurkalova, Kling, and Zhao, 2006; Davey and Furtan, 2008). Our findings on the statistically significant, negative effect of $FLOOD$ on the CT adoption complement those of Ding, Schoengold, and Tadesse (2009), who used county-level data covering Iowa, Nebraska, and South Dakota to show a link between droughts (or spring floods) and increased (or decreased) use of CT. Our results confirm the identified relationships between the soil wetness extremes and CT for Iowa.

The aggregated, county-level and time-invariant nature of our farmer characteristics data does not support strong conclusions about the impact of these independent variables on adoption, but our results suggest that the adoption premium is higher (and the probability of adoption is lower) for more experienced, male farmers. The impacts of farm and operator characteristics on the adoption of conservation practices are mixed in the literature. The hypothesis that more experienced farmers are more likely to utilize CT mechanisms has some support in empirical studies (Kurkalova, Kling, and Zhao, 2006; Knowler and Bradshaw, 2007). However, our results suggest that older farmers are more risk averse because they may not want to make changes to management practices late in their careers (Marland, McCarl, and Schneider, 2001).

In our study, the county-average proportion of farms operating as family-held corporations to the total county farms, $CORP$, has a statistically strong positive effect on adoption, indicating that the farm's organizational type does play into the tillage decision. However, this result must be taken with caution, as the variable may be capturing the farm size effect since corporations tend to be, on average, larger than the other farms (U.S. Department of Agriculture, National Agricultural Statistical Service, 2004). The literature suggests that larger farms are more likely to adopt new technologies than smaller farms (Fuglie, 1999; Soule, Tegene, and Wiebe, 2000; Fuglie and Kascak, 2001; Lambert et al., 2007; Davey and Furtan, 2008). Several studies have argued that high per acre costs and the associated higher financial risks incurred by smaller farms impede CT adoption (Lee and Stewart, 1983). If, as we surmise, size and organizational type have similar effects on CT adoption, our findings imply that smaller family or individual farms need greater incentives to switch to CT than larger farms. However, meaningful distinction between the effect of organizational structure and size may be challenging since the Census of Agriculture statistics on farm size are also aggregated to the county level.

Field-Specific Costs of Conservation Tillage Adoption

Using the estimation results from table 3 and equation (2), we predict the costs of CT adoption at every field. The modeling approach, though borrowed from Kurkalova, Kling, and Zhao (2006), adds value in that these field-specific cost estimates result from aggregated data and are derived from the latest county-level CT data available, 2002–2004. We estimate the sample average cost of CT adoption to be \$13/acre, which is akin to the costs estimated by Kurkalova, Kling, and Zhao (2006)

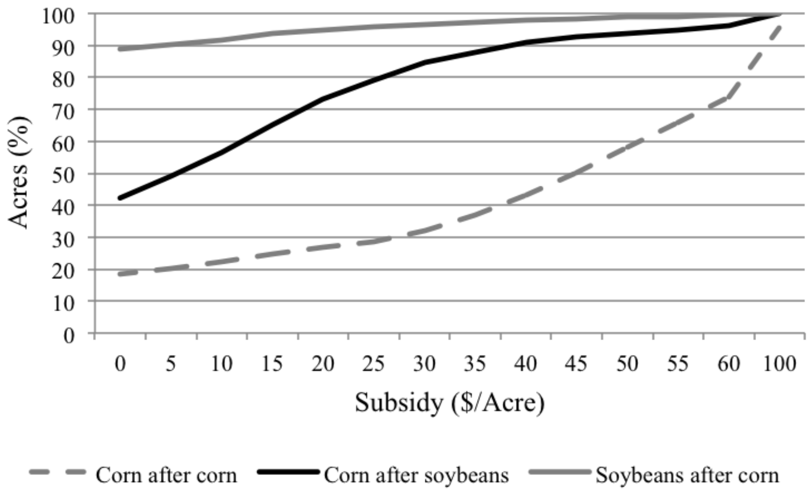

Figure 1. Potential Increase in Land in Conservation Tillage in Response to Subsidies

and De La Torre Ugarte, Hellwinckel, and Larson (2004). The weighted averages of the field-level costs are estimated as $43/acre for CC (standard deviation $31) versus $14/acre (standard deviation $19) for CS. The large standard deviations are not surprising given that the subsidy is zero for those already using CT. Remarkably, our results imply the same, approximately threefold increase in the cost of CT adoption for corn after corn when compared to corn after soybeans that De La Torre Ugarte, Hellwinckel, and Larson (2004) found using agronomic controlled experiments data and an economic model that simulates tillage choices of risk-averse farmers. To our knowledge, the CT adoption cost comparisons by crop and previous crop from observed (rather than from simulated) data have not been reported in the literature. As expected, the average soybeans costs, $3/acre (standard deviation $10), are the lowest of the three cropping sequences. Soybean yields are unaffected by tillage mechanisms, and therefore CT lowers production costs without affecting yields (Yin and Al-Kaisi, 2004).

We estimate that 18% of CC, 42% of CS, and 89% of SC acres farmed in 2002 and 2004 do not require subsidies to use CT. Figure 1 illustrates the differences between cropping sequences in the rate of increase in CT adoption in response to the subsidies. Particularly noteworthy are the relatively high costs of obtaining additional CT acres in CC fields as well as the small change in the percentage of soybean acres in response to CT adoption subsidies. In 2002 and 2004, it would have cost approximately $52.4 million, or up to $45/acre, to achieve a 50% adoption of CT on CC fields versus $2.5 million, or up to $5/acre, to achieve the same on CS fields. These findings underscore the importance of accounting for not only crop but also for rotation when evaluating cropland-based climate change mitigation offset programs. The estimated state-average costs of CT adoption for current users of conventional tillage are $23 (standard deviation $18) for SC, $24 (standard deviation $19) for CS, and $52 (standard deviation $25) for CC.

Observing the spatial heterogeneity of adoption subsidies provides researchers and policy makers with the tools needed to create flexible policies that best suit their constituencies. Figure 2 provides examples of the variation in nonadopter costs within a single county (Woodbury) for CS (a) and CC (b). SC rotations are omitted since a majority of these fields already adopt CT leaving few observations for analysis. Often, stakeholders are only provided with averages or medians. For Woodbury county, the mean subsidy for CC is $73 and the mean subsidy for CS is $48. Here we see that taking the averages of the estimated subsidies grossly overestimates and underestimates what many farmers are predicted to accept to use CT. A simple county average will clearly create inefficiencies in conservation programs since overpaying farmers who will accept less to adopt leaves fewer resources available to entice those who require much higher subsidies.

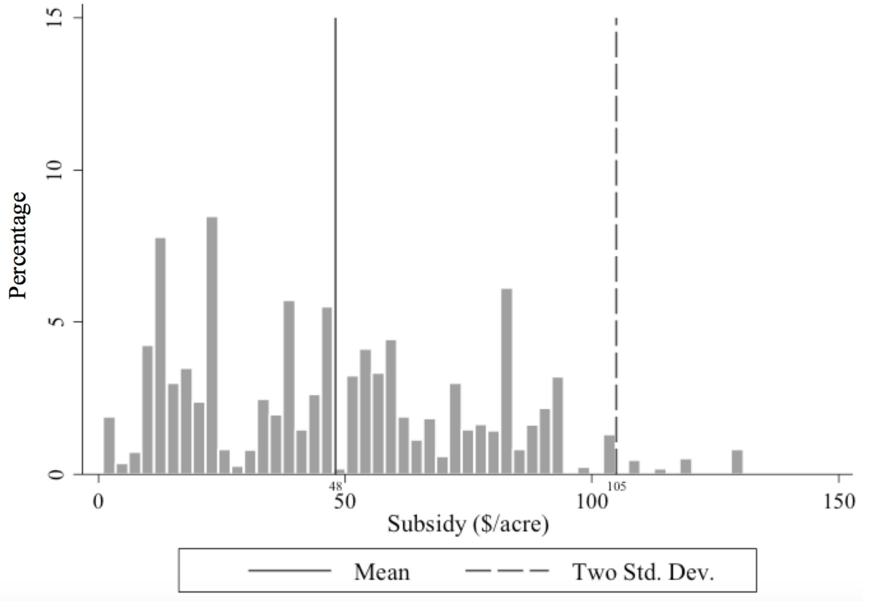

Figure 2a. Distribution of Estimated Subsidies for Corn Following Soybean Fields in Conventional Tillage for Woodbury County

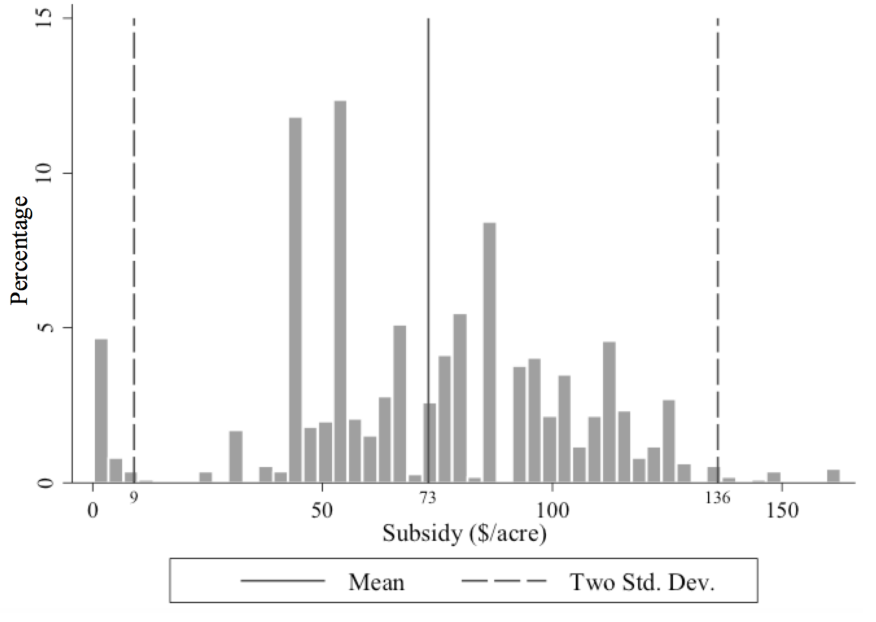

Figure 2b. Distribution of Estimated Subsidies for Corn Following Corn Fields in Conventional Tillage for Woodbury County

Similar to Kurkalova and Kling (2002), we find that CT is more costly to implement in the areas with relatively high productivity and cool climate. We also find relatively high CT adoption costs for the counties on the east central and the west central borders of the state.[9] These counties are well known for both highly productive soils (see Johanns, 2011a,b) and hilly landscapes, especially along the Missouri and Mississippi rivers. The highly sloped fields are likely to be classified as HEL and, consequently, farmed using no-till and ridge-till systems. However, once the highly sloped, CT-farmed fields are removed from consideration, the acreage left represents more evenly sloped fields with highly productive soils that require relatively high subsidies for conversion to CT. The estimation of the field-level model of CT adoption allows the separation of nonadopters from the adopters within a county and highlights the impacts of natural resource differences on the use and the costs of this farming practice. Since prices are generally homogeneous across the state and many of the explanatory variables used in this study, such as soil structure and climate, change little over short periods, the county-relative-to-state relationships we have identified may hold true for today's nonadopters.

Conclusions

The mismatch between detailed GIS-based land use data and aggregated data on conservation practices as well as the lack of availability of field- or farm-level practice data results in the need to develop econometric models that work with aggregated data and are consistent with underlying rational decision-making at a disaggregated scale. This article presents an application of the GDVL modeling approach to estimate the costs of CT for Iowa. The model relies on interpreting the county average proportion of land in CT as an expected value of a binary choice variable and allows full recovery of the parameters of a logit function representing the CT adoption decision at a field scale even though the information on adoption is available only in aggregated form.

We find that the average 2002–2004 costs of CT adoption are \$13/acre. Our results indicate a three-fold increase in the costs of CT use between corn monoculture and rotated corn. This is the first estimate from observed behavioral data. Previous studies only used simulation models applied to controlled agronomic experiments data (De La Torre Ugarte, Hellwinckel, and Larson, 2004). Our findings have important policy implications because of current ethanol policies and the overall recent growth in continuous corn acreage (Stern, Doraiswamy, and Akhmedov, 2008). The estimates developed here provide empirical support for the argument that farmers who have strong economic goals may simply not buy into conservation programs unless properly compensated (Sheeder and Lynne, 2011; Ma et al., 2012).

The results presented illustrate the extent of within-county heterogeneity of adoption costs. Aggregating subsidy estimates handicaps policy makers seeking to develop creative and efficient conservation programs in their constituencies. This is especially true for counties that have mixed topography and soils. Knowing the distributions of costs is of vital importance for cost-effective design of incentive-based conservation policies (Horan and Claassen, 2007). Estimated field-level choices can be incorporated into policy analysis and program design. For example, they can be used to (1) create bid ceilings based on soil and climate properties as opposed to asking the farmer what he/she is willing to accept, (2) offer additional incentives to farmers who have physical barriers to adoption like poorly drained soil or limited cropland, (3) set subsidy rates based on adoption of other management practices, or (4) create conservation point systems based ratios driven by the coefficients of models that combine physical and economic attributes as opposed to arbitrary linear point systems. Simple criteria (based on attributes of interest placed in the model) may be used to create algorithms that policy makers can use to design programs.

[9] Figures depicting the differences between estimated county-average and state-average costs of CT for the current nonadopters and for CS, CC, and SC are available upon request.

As with any empirical work, our results are contingent on the available data. Using less aggregated farm and farm operator characteristics data will likely improve subsidy estimates. Also, the estimates obtained do not account for current payments for CT adoption available through programs like EQIP and the Conservation Stewardship Program. Information on payments made for practices, even at an aggregated level, will improve costs estimates of CT adoption and, consequently, improve policy analyses.

The CT adoption function estimates provided here can be directly applied to fit theoretical models to large landscapes (Wilman, 2011) and alternative economic conditions and land use patterns to evaluate the field's suitability for CT adoption, potential CT profits, the likelihood of CT adoption, and magnitudes of the subsidies needed to induce the use of CT. For example, given appropriate net returns data, future research could test the hypothesis that increasing energy prices are likely to increase the use of CT (Center for Agricultural Science and Technology, 2012), or the reverse hypothesis that, as energy prices increase, CT subsidies will need to increase. This would be the case if increases in energy prices increased corn prices, since CT for CC is more challenging and expensive for farmers (Secchi et al., 2008). While subsidies are administered on the macro scale, it is important to note that the majority of the underlying drivers to adoption occur on the micro scale. These micro-level decisions will need to be analyzed if the environmental programs are going to have continued or improved success.

The econometric model presented here can also be applied to evaluate the costs of adopting other conservation practices, such as terraces or cover crops. With appropriate changes to the specification, the model can estimate the cost of adopting conservation practices in other regions and with alternative cropping systems. The demand for field-level data and models of conservation practices use comes from the recognition that (even on the same farm) the environmental outcomes of crop production can vary widely and integrated economic and biophysical process models need field-level inputs (Howitt and Reynaud, 2003; Papalia, 2010; Aurbacher and Dabbert, 2011).

Finally, the estimates we obtain and the modeling approach we use are also contributing to the sparse but growing literature on spatial disaggregation methods consistent with the underlying micro-level economic behavior (Miller and Plantinga, 1999; Howitt and Reynaud, 2003; You and Wood, 2006; Chakir, 2009; Gerlt, Thompson, and Miller, 2014). An in-depth comparison of the disaggregation technique stemming from our estimation approach with the known disaggregation methodologies commonly rooted in maximum entropy framework is left for future research.

[Received July 2015; final revision received March 2016.]

References

Al-Kaisi, M., and X. Yin. “Stepwise Time Response of Corn Yield and Economic Return to No Tillage.” *Soil and Tillage Research* 78(2004):91–101. doi: 10.1016/S0167-1987(04)00048-0.

Archer, D. W., and J. M. F. Johnson. “Evaluating Local Crop Residue Biomass Supply: Economic and Environmental Impacts.” *BioEnergy Research* 5(2012):699–712. doi: 10.1007/s12155-012-9178-2.

Aurbacher, J., and S. Dabbert. “Generating Crop Sequences in Land-Use Models using Maximum Entropy and Markov Chains.” *Agricultural Systems* 104(2011):470–479. doi: 10.1016/j.agsy.2011.03.004.

Baird, R. E., B. G. Mullinix, A. B. Peery, and M. L. Lang. “Diversity and Longevity of the Soybean Debris Mycobiota in a No-Tillage System.” *Plant Disease* 81(1997):530–534. doi: 10.1094/PDIS.1997.81.5.530.

Baker, N. T. “Tillage Practices in the Conterminous United States, 1989–2004—Datasets Aggregated by Watershed.” Data Series 573, National Water-Quality Assessment Program Prepared in cooperation with the Conservation Technology Information Center, Reston, VA, 2011. Available online at http://pubs.usgs.gov/ds/ds573/.

Banerjee, S., S. W. Martin, R. K. Roberts, J. A. Larson, R. J. Hogan, J. L. Johnson, K. W. Paxton, and J. M. Reeves. “Adoption of Conservation-Tillage Practices and Herbicide-Resistant Seed in Cotton Production.” *AgBioForum* 12(2009):258–268.

Bricklemyer, R. S., R. L. Lawrence, P. R. Miller, and N. Battogtokh. “Predicting Tillage Practices and Agricultural Soil Disturbance in North Central Montana with Landsat Imagery.” *Agriculture, Ecosystems & Environment* 114(2006):210–216. doi: 10.1016/j.agee.2005.10.005.

Center for Agricultural Science and Technology. “Carbon Sequestration and Greenhouse Gas Fluxes in Agriculture: Challenges and Opportunities.” Task Force Report 142, Center for Agricultural Science and Technology, Ames, IA, 2011. Available online at http://www.cast-science.org/publications/index.cfm/carbon_sequestration_and_greenhouse_gas_fluxes_in_agriculture_challenges_and_opportunities?show=product&productID=27392.

———. “Energy Issues Affecting Corn/Soybean Systems: Challenges for Sustainable Production.” Issue Paper 48-QC, Center for Agricultural Science and Technology, Ames, IA, 2012. Available online at http://www.cast-science.org/publications/?energy_issues_affecting_cornsoybean_systems_challenges_for_sustainable_production&show=product&productID=52665.

Chakir, R. “Spatial Downscaling of Agricultural Land-Use Data: An Econometric Approach Using Cross Entropy.” *Land Economics* 85(2009):238–251. doi: 10.3368/le.85.2.238.

Claassen, R., A. Cattaneo, and R. Johansson. “Cost-Effective Design of Agri-Environmental Payment Programs: U.S. Experience in Theory and Practice.” *Ecological Economics* 65(2008):737–752. doi: 10.1016/j.ecolecon.2007.07.032.

Claassen, R., and R. E. Just. “Heterogeneity and Distributional Form of Farm-Level Yields.” *American Journal of Agricultural Economics* 93(2011):144–160. doi: 10.1093/ajae/aaq111.

Conservation Technology Information Center. “Crop Residue Management Survey.” 2012a. West Lafayette, IN. Available online at http://www.ctic.org/resourcedisplay/255/.

———. “Tillage Type Definitions.” 2012b. West Lafayette, IN. Available online at http://www.ctic.purdue.edu/media/pdf/TillageDefinitions.pdf.

Cooper, J. “Combining Actual and Contingent Behavior Data to Model Farmer Adoption of Water Quality Protection Practices.” *Journal of Agricultural and Resource Economics* 22(1997):56–64.

Cooper, J. C., and G. Signorello. “Farmer Premiums for the Voluntary Adoption of Conservation Plans.” *Journal of Environmental Planning and Management* 51(2008):1–14. doi: 10.1080/09640560701712234.

Davey, K. A., and W. H. Furtan. “Factors that Affect the Adoption Decision of Conservation Tillage in the Prairie Region of Canada.” *Canadian Journal of Agricultural Economics* 56(2008):257–275. doi: 10.1111/j.1744-7976.2008.00128.x.

De La Torre Ugarte, D. G., C. M. Hellwinckel, and J. A. Larson. “Enhancing Agriculture’s Potential to Sequester Carbon: A Framework to Estimate Incentive Levels for Reduced Tillage.” *Environmental Management* 33(2004):S229–S237. doi: 10.1007/s00267-003-9133-2.

Ding, Y., K. Schoengold, and T. Tadesse. “The Impact of Weather Extremes on Agricultural Production Methods: Do Extreme Weather Events Increase Adoption of Conservation Tillage Practices?” *Journal of Agricultural and Resource Economics* 34(2009):395–411.

Duffy, M., and D. Smith. “Estimated Costs of Crop Production in Iowa – 2002.” Fm-1712, Iowa State University Extension, Ames, IA, 2002. Available online at http://www2.econ.iastate.edu/faculty/duffy/Pages/2002FM1712.pdf.

———. “Estimated Costs of Crop Production in Iowa – 2004.” Fm-1712, Iowa State University Extension, Ames, IA, 2004. Available online at http://www2.econ.iastate.edu/faculty/duffy/Pages/2004FM1712.pdf.

Fuglie, K. O. “Conservation Tillage and Pesticide Use in the Cornbelt.” *Journal of Agricultural and Applied Economics* 31(1999):133–147.

Fuglie, K. O., and D. J. Bosch. “Economic and Environmental Implications of Soil Nitrogen Testing: A Switching-Regression Analysis.” *American Journal of Agricultural Economics* 77(1995):891–900. doi: 10.2307/1243812.

Fuglie, K. O., and C. A. Kascak. “Adoption and Diffusion of Natural-Resource-Conserving Agricultural Technology.” *Review of Agricultural Economics* 23(2001):386–403. doi: 10.1111/1467-9353.00068.

Gerlt, S., W. Thompson, and D. Miller. “Exploiting the Relationship between Farm-Level Yields and County-Level Yields for Applied Analysis.” *Journal of Agricultural and Resource Economics* 39(2014):253–270.

Giannakas, K., and J. D. Kaplan. “Policy Design and Conservation Compliance on Highly Erodible Lands.” *Land Economics* 81(2005):20–33. doi: 10.3368/le.81.1.20.

Hennessy, D. A. “On Monoculture and the Structure of Crop Rotations.” *American Journal of Agricultural Economics* 88(2006):900–914. doi: 10.1111/j.1467-8276.2006.00905.x.

Horan, R. D., and R. Claassen. “Targeting Green Payments under a Budget Constraint.” *Land Economics* 83(2007):319–330. doi: 10.3368/le.83.3.319.

Horowitz, J., R. Ebel, and K. Ueda. “No-Till Farming Is a Growing Practice.” Economic Information Bulletin 70, U.S. Deptartment of Agriculture, Economic Research Service, Washington, DC, 2010. Available online at http://www.ers.usda.gov/media/135329/eib70.pdf.

Howitt, R., and A. Reynaud. “Spatial Disaggregation of Agricultural Production Data Using Maximum Entropy.” *European Review of Agricultural Economics* 30(2003):359–387. doi: 10.1093/erae/30.3.359.

Iowa State University. *Iowa Soil Properties and Interpretations Database (ISPAID) version 7.0*. Ames, IA: Cooperative Soil Survey Iowa Agriculture and Home Economics Experiment Station, 2004. Available online at http://www.extension.iastate.edu/soils/ispaid.

Johanns, A. “Historical Corn Yields by County.” Ag Decision Maker File A1-12, Iowa State University Extension and Outreach, Ames, IA, 2011a. Available online at https://www.extension.iastate.edu/agdm/crops/pdf/a1-12.pdf.

———. “Historical Soybean Yields by County.” Ag Decision Maker File A1-13, Iowa State University Extension and Outreach, Ames, IA, 2011b. Available online at https://www.extension.iastate.edu/agdm/crops/pdf/a1-13.pdf.

———. “Iowa Cash Corn and Soybean Prices.” Ag Decision Maker File A2-11, Iowa State University Extension and Outreach, Ames, IA, 2011c. Available online at https://www.extension.iastate.edu/agdm/crops/pdf/a2-11.pdf.

Just, R. “Some Guiding Principles for Empirical Production Research in Agriculture.” *Agricultural and Resource Economics Review* 29(2000):138–158.

Karlen, D. L., R. Lal, R. F. Follett, J. M. Kimble, J. L. Hatfield, J. M. Miranowski, C. A. Cambardella, A. Manale, R. P. Anex, and C. W. Rice. "Crop Residues: The Rest of the Story." *Environmental Science & Technology* 43(2009):8011–8015. doi: 10.1021/es9011004.

Khanna, M., X. Chen, H. Huang, and H. Önal. "Supply of Cellulosic Biofuel Feedstocks and Regional Production Pattern." *American Journal of Agricultural Economics* 93(2011):473–480. doi: 10.1093/ajae/aaq119.

Knowler, D., and B. Bradshaw. "Farmers' Adoption of Conservation Agriculture: A Review and Synthesis of Recent Research." *Food Policy* 32(2007):25–48. doi: 10.1016/j.foodpol.2006.01.003.

Kurkalova, L., and C. Kling. "Incentives to Boost Conservation Tillage Adoption." *Iowa Ag Review* 8(2002):11–12.

Kurkalova, L., C. Kling, and J. Zhao. "Green Subsidies in Agriculture: Estimating the Adoption Costs of Conservation Tillage from Observed Behavior." *Canadian Journal of Agricultural Economics* 54(2006):247–267. doi: 10.1111/j.1744-7976.2006.00048.x.

Kurkalova, L. A., and S. S. Rabotyagov. "Estimation of a Binary Model with Grouped Choice Data." *Economics Letters* 90(2006):170–175. doi: 10.1016/j.econlet.2005.07.022.

Kurkalova, L. A., S. Secchi, and P. W. Gassman. "Corn Stover Harvesting: Potential Supply and Water Quality Implications." In M. Khanna, J. Scheffran, and D. Zilberman, eds., *Handbook of Bioenergy Economics and Policy,* No. 33 in Natural Resource Management and Policy. New York: Springer, 2010, 307–323. doi: 10.1007/978-1-4419-0369-3_18.

Kurkalova, L. A., and T. Wade. "Aggregated Choice Data and Logit Models: Application to Environmental Benign Practices of Conservation Tillage by Farmers in the United States." *Applied Econometrics and International Development* 13(2013):119–128.

Lambert, D., G. D. Schaible, R. Johansson, and U. Vasavada. "The Value of Integrated CEAP-ARMS Survey Data in Conservation Program Analysis." *Journal of Soil and Water Conservation* 62(2007):1–10.

Lee, L. K., and W. H. Stewart. "Landownership and the Adoption of Minimum Tillage." *American Journal of Agricultural Economics* 65(1983):256–264. doi: 10.2307/1240871.

Lichtenberg, E. "Cost-Responsiveness of Conservation Practice Adoption: A Revealed Preference Approach." *Journal of Agricultural and Resource Economics* 29(2004):420–435.

Lichtenberg, E., J. Shortle, J. Wilen, and D. Zilberman. "Natural Resource Economics and Conservation: Contributions of Agricultural Economics and Agricultural Economists." *American Journal of Agricultural Economics* 92(2010):469–486. doi: 10.1093/ajae/aaq006.

Ma, S., S. M. Swinton, F. Lupi, and C. Jolejole-Foreman. "Farmers' Willingness to Participate in Payment-for-Environmental-Services Programmes." *Journal of Agricultural Economics* 63(2012):604–626. doi: 10.1111/j.1477-9552.2012.00358.x.

Marland, G., B. A. McCarl, and U. Schneider. "Soil Carbon: Policy and Economics." *Climatic Change* 51(2001):101–117. doi: 10.1023/A:1017575018866.

Miller, D. J., and A. J. Plantinga. "Modeling Land Use Decisions with Aggregate Data." *American Journal of Agricultural Economics* 81(1999):180–194. doi: 10.2307/1244459.

Napier, T. L., and M. Tucker. "Use of Soil and Water Protection Practices among Farmers in Three Midwest Watersheds." *Environmental Management* 27(2001):269–279. doi: 10.1007/s002670010148.

National Climatic Data Center. *Data Documentation for Data Set 3200 (DSI-3200): Surface Land Daily Cooperative Summary of the Day*. Asheville, NC: National Climatic Data Center, 2010. Available online at http://www1.ncdc.noaa.gov/ pub/ data/documentlibrary/tddoc/td3200.pdf.

Papalia, R. B. "Data Disaggregation Procedures within a Maximum Entropy Framework." *Journal of Applied Statistics* 37(2010):1947–1959. doi: 10.1080/02664760903199489.

Pautsch, G., L. Kurkalova, B. Babcock, and C. Kling. "The Efficiency of Sequestering Carbon in Agricultural Soils." *Contemporary Economic Policy* 19(2001):123–134. doi: 10.1111/j.1465-7287.2001.tb00055.x.

Prokopy, L. S., K. Floress, D. Klotthor-Weinkauf, and A. Baumgart-Getz. "Determinants of Agricultural Best Management Practices Adoption: Evidence from the Literature." *Journal of Soil and Water Conservation* 63(2008):300–311. doi: 10.2489/jswc.63.5.300.

Secchi, S., P. W. Gassman, J. R. Williams, and B. A. Babcock. "Corn-Based Ethanol Production and Environmental Quality: A Case of Iowa and the Conservation Reserve Program." *Environmental Management* 44(2009):732–744. doi: 10.1007/s00267-009-9365-x.

Secchi, S., L. Kurkalova, P. W. Gassman, and C. Hart. "Land Use Change in a Biofuels Hotspot: The Case of Iowa, USA." *Biomass and Bioenergy* 35(2011):2391–2400. doi: 10.1016/j.biombioe.2010.08.047.

Secchi, S., J. Tyndall, L. A. Schulte, and H. Asbjornsen. "High Crop Prices and Conservation Raising the Stakes." *Journal of Soil and Water Conservation* 63(2008):68A–73A. doi: 10.2489/jswc.63.3.68A.

Shaw, D., S. Culpepper, M. Owen, A. Price, and R. Wilson. "Herbicide-Resistant Weeds Threaten Soil Conservation Gains: Finding a Balance for Soil and Farm Sustainability." Issue Paper 49, Council for Agricultural Science and Technology, Ames, IA, 2012. Available online at http://www.cast-science.org/publications/?herbicideresistant_weeds_threaten_soil_conservation_gains_finding_a_balance_for_soil_and_farm_sustainability&show=product&productID=52723.

Sheeder, R. J., and G. D. Lynne. "Empathy-Conditioned Conservation: "Walking in the Shoes of Others" as a Conservation Farmer." *Land Economics* 87(2011):433–452. doi: 10.3368/le.87.3.433.

Skaggs, R. K., R. E. Kirksey, and W. M. Harper. "Determinants and Implications of Post-CRP Land Use Decisions." *Journal of Agricultural and Resource Economics* 19(1994):299–312.

Smith, K. R. "Federal Statistics for Applied Economists." *Choices* 28(2013):1–5.

Soule, M. J., A. Tegene, and K. D. Wiebe. "Land Tenure and the Adoption of Conservation Practices." *American Journal of Agricultural Economics* 82(2000):993–1005. doi: 10.1111/0002-9092.00097.

Stern, A. J., P. C. Doraiswamy, and B. Akhmedov. "Crop Rotation Changes in Iowa Due to Ethanol Production." In *IGARSS 2008 - 2008 IEEE International Geoscience and Remote Sensing Symposium,* vol. 5. Boston, MA: IEEE, 2008, 200–203.

Thoma, D. P., S. C. Gupta, and M. E. Bauer. "Evaluation of Optical Remote Sensing Models for Crop Residue Cover Assessment." *Journal of Soil and Water Conservation* 59(2004):224–233.

Triplett, G. B., and W. A. Dick. "No-Tillage Crop Production: A Revolution in Agriculture!" *Agronomy Journal* 100(2008):S153–S165. doi: 10.2134/agronj2007.0005c.

U.S. Department of Agriculture, Economic Research Service. "Farm Resource Regions." Agriculture Information Bulletin 760, U.S. Department of Agriculture, Washington, DC, 2000. Available online at http://www.ers.usda.gov/publications/aib-agricultural-information-bulletin/aib760.aspx.

U.S. Department of Agriculture, National Agricultural Statistical Service. "Part 15: Geographic Area Series." In *Census of Agriculture: Volume 1,* Washington, DC: U.S. Department of Agriculture, 2004. Available online at https://www.agcensus.usda.gov/Publications/2002/index.php.

U.S. Department of Agriculture, National Agricultural Statistics Service. "Field Crops Usual Planting and Harvesting Dates." Agricultural Handbook 628, U.S. Department of Agriculture, Washington, DC, 2010. Available online at http://usda.mannlib.cornell.edu/usda/current/planting/planting-10-29-2010.pdf.

———. *Quick Stats*. Washington, DC: U.S. Department of Agriculture, 2013. Available online at http://www.nass.usda.gov/Quick_Stats/.

U.S. Department of Agriculture, National Agricultural Statistics Service, Research and Development Division, Research and Development Division, Geospatial Information Branch, Spatial Analysis Research Section. *2002–2004 Iowa Cropland Data Layer*. Washington, DC: U.S. Department of Agriculture, 2010.

U.S. Department of Agriculture, National Resource Conservation Service. *Highly Erodible Land Conservation Compliance Provisions: Key Points*. Washington, DC: U.S. Department of Agriculture, 2002. Available online at https://prod.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs143_007707.pdf.

U.S. Department of Agriculture, National Resources Conservation Service. *Assessment of the Effects of Conservation Practices on Cultivated Cropland in the Upper Mississippi River Basin. Conservation Effects Assessment Project*. Washington, DC: U.S. Department of Agriculture, 2012. Available online at http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1042093.pdf.

Wilman, E. A. "Carbon Sequestration in Agricultural Soils." *Journal of Agricultural and Resource Economics* 36(2011):121–138.

Workneh, F., G. L. Tylka, X. B. Yang, J. Faghihi, and J. M. Ferris. "Regional Assessment of Soybean Brown Stem Rot, *Phytophthora sojae* , and *Heterodera glycines* Using Area-Frame Sampling: Prevalence and Effects of Tillage." *Phytopathology* 89(1999):204–211. doi: 10.1094/PHYTO.1999.89.3.204.

Wu, J., R. M. Adams, C. L. Kling, and K. Tanaka. "From Microlevel Decisions to Landscape Changes: An Assessment of Agricultural Conservation Policies." *American Journal of Agricultural Economics* 86(2004):26–41. doi: 10.1111/j.0092-5853.2004.00560.x.

Wu, J., and B. A. Babcock. "The Choice of Tillage, Rotation, and Soil Testing Practices: Economic and Environmental Implications." *American Journal of Agricultural Economics* 80(1998):494–511. doi: 10.2307/1244552.

Yin, X., and M. M. Al-Kaisi. "Periodic Response of Soybean Yields and Economic Returns to Long-Term No-Tillage." *Agronomy Journal* 96(2004):723–733. doi: 10.2134/agronj2004.0723.

You, L., and S. Wood. "An Entropy Approach to Spatial Disaggregation of Agricultural Production." *Agricultural Systems* 90(2006):329–347. doi: 10.1016/j.agsy.2006.01.008.

Zheng, B., J. B. Campbell, G. Serbin, and C. S. T. Daughtry. "Multitemporal Remote Sensing of Crop Residue Cover and Tillage Practices: A Validation of the minNDTI Strategy in the United States." *Journal of Soil and Water Conservation* 68(2013):120–131. doi: 10.2489/jswc.68.2.120.