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Using the logit model with aggregated choice data in estimation of Iowa corn farmers' conservation tillage subsidies

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Abstract

This study estimates the costs of adoption of conservation tillage by Iowa corn farmers by utilizing the method of empirical estimation of a logit model that incorporates the full information on the attributes of agents 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 the 2002 and 2004 county-average conservation tillage choice data, we estimate field level costs of the adoption of conservation tillage and predict that the sample average subsidy payment required to entice farmers to use conservation tillage is \$17.65/acre. The results indicate that conservation tillage adoption is significantly affected by soil characteristics, crop choice and high net returns using conventional tillage methods.

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. Some of its benefits, when compared to conventional tillage, are in the protection of soil from excessive rain, wind, and sunlight. CT has been shown to improve soil structure, reduce soil temperature and evaporation, increase infiltration, and reduce nutrient runoff and erosion (Uri 2000b; Sullivan 2003; Brickleyer et al. 2006; Williams et al. 2007; Tomer et al. 2008; Shaw et al. 2012). The use of CT also contributes to soil organic matter and nutrient availability, water retention, macro-invertebrate activity (Wilhelm et al. 2004; Soil Quality National Technology Department Team 2006) and carbon sequestration (Marland, McCarl and Schneider 2001; Kim and Dale 2005; Huggins et al. 2007). From the farmer's perspective, to be accepted, CT must adequately control soil erosion, conserve

moisture, accommodate the crops grown and not adversely affect profits (Mannering and Fenster 1983, McConnell 1983).

While there may be some dissent (see Baker et al. (2007)), agricultural cropland is widely thought to have great potential for the expansion of carbon sequestration (Marland, McCarl and Schneider 2001) and has been targeted in this effort (Horowitz, Ebel and Ueda 2010). Tillage reduction is one management decision that can be applied by several farms and hence on several acres of cropland and is therefore viewed by policymakers as a feasible means of achieving carbon sequestration and other soil conservation goals. Since the benefits of CT accrue to the society at large rather than exclusively to the farmer, there is discussion as to how to achieve societal conservation goals without depending solely on farmer stewardship. Horowitz, Ebel and Ueda (2010) discusses two feasible policy ideas that may achieve conservation goals by appealing to farmers' profit maximizing agenda. Initiatives such as cap-and-trade have the potential to encourage farmers to adopt environmentally healthy soil practices by awarding agents offsets credits which may then be sold to industrial sources of greenhouse gas emissions. Another proposal is to design programs (like the Environmental Quality Incentives Program) that offer incentive payments to agents who willingly adopt CT.

This article is motivated by programs that offer incentives (or subsidies) for CT use. Maximizing the environmental benefits per dollar of subsidy will be one major component of a successful program scheme (Claassen, Cattaneo, and Johansson 2008). In terms of CT adoption, this means making the minimum payment necessary to achieve CT acreage. A key component in this effort is land heterogeneity as it determines both costs and environmental benefits of adoption. Therefore, incorporating detailed soil characteristics and management choices made on

plots of land allows policymakers to target CT payments to parcels that may yield the greatest environmental benefits (Claassen, Cattaneo, and Johansson 2008).

Numerous economic studies have been conducted on the adoption of CT that conclude farmers can be persuaded to use conservation practices with incentive payments (e.g. Ervin and Ervin (1982), Rahm and Huffman (1984) and Fuglie (1999)), but few have actually quantified these incentive payments using econometric estimation techniques (see De La Torre Ugarte, Hellwinckel, and Larson (2004), Wu et al. (2004) and Kurkalova, Kling, and Zhao (2006)). Confidentiality and cost concerns may limit the collection of the farm-level data needed for such studies (Fletcher and Phipps 1991; Rubin 1993; Freedman 1999; McClelland and Horowitz 1999; Howitt and Reynaud 2003; Schmit, Rounsevell, and Jeunesse 2006; Banerjee et al. 2009), resulting in a shortage of farm-level survey data. Researchers are therefore, often turned to the use of data that have been aggregated to regional levels (see Miller and Plantinga 1999; Antle et al. 2007; West et al. 2008; Ding, Schoengold and Tadesse 2009) knowing that doing so may introduce bias in the coefficient estimators (Hellerstein 2005).

However, as micro-level data such as GIS, soil survey and satellite imagery become increasingly available to researchers through the US Department of Agriculture, National Agricultural Statistics Service (USDA, NASS) there is a drive in the agriculture and conservation literature to utilize these rich data sources despite having spatially incompatible farm data. This desire has led to the development of models such as those found in Howitt and Reynaud (2003), Kempen et al. (2005), You and Wood (2006), McClean (2007), Chakir (2009), Papalia (2010) and Aurbacher and Dabbert (2011) that disaggregate land use data to a smaller scale. Howitt and Reynaud (2003) makes three compelling arguments for disaggregating data: (1) the unavailability of spatially fine data has pushed researchers to use aggregated data to estimate

relationships that are defined at more disaggregated level, (2) the desire to utilize biophysical models and (3) disaggregating data is far less expensive than collecting micro-level data. Therefore, even with the aggregate data, it is highly desirable to have as detailed micro-models as possible. The connection between biophysical and agricultural data shows immense promise in conservation research as it allows for complex and comprehensive economic models of agriculture and environmental benefits that may be used in the design of cost effective conservation programs (Claassen 2009).

This study estimates the costs of CT adoption by Iowa corn farmers by using the maximum likelihood method to estimate a discrete choice model with aggregate choice data. We use the Group Dependent Variable Logistic (GDVL) model (Wade 2011) that treats the aggregated data as an expected value—the crop and county area-weighted average of individual probabilities of choosing CT subject to measurement error. The algorithm we present recovers the parameters of interest needed to understand the economic drivers as well as quantifies the variation in the normal and logistic errors.

To make best use of the available data, the aggregated CT choice data are married with field and county level choice determinants. The use of the GDVL model on the combined aggregated and disaggregated data allows one to estimate field-level responsiveness to CT adoption incentives. The parameter estimates are then used to estimate the minimum field-level incentives required for CT adoption. Subsidies are estimated using the most recent CT use data available at the county level through the CTIC (<http://www.ctic.purdue.edu/>), that for the years 2002 and 2004. Making these estimates some of the most recently available. In addition to the subsidy estimation we are particularly interested in how the rotation (or cropping sequence) decision affects the tillage decision and examine the hypothesis that for farmers it is not only the

crop that is grown but more specifically, the rotation that the farmer chooses that affects tillage choice.

The rest of the paper is organized as follows. We first present the economic model of CT use and the GDVL econometric model. Subsequent sections detail the data used for the empirical estimation and econometric estimation results. We then discuss the results and offer a few concluding remarks.

Economic Model of Conservation Tillage Adoption

In modeling the adoption of CT we follow the approach of Kurkalova, Kling, and Zhao (2006), which assumes that a farmer will adopt CT when the expected net returns from this farming practice exceed the sum of those from conventional tillage and the adoption premium, with the latter attributed to the uncertainty in the CT returns. 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 the researchers. Let Y be the observable binary variable representing the adoption of CT, i.e., $Y = 1$ if a farmer uses CT, and zero otherwise. From the researchers' perspective, the probability of CT adoption is written as

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

where $\boldsymbol{\alpha}'\mathbf{w}$ 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, \mathbf{w} , $\boldsymbol{\gamma}'\mathbf{z}$ represents the premium as a function of the unknown vector of parameters, $\boldsymbol{\gamma}$, and the observed vector of explanatory variables, \mathbf{z} , η is a logistic error reflecting the researchers' ignorance about the exact relationship between the expected net returns to conservation tillage 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 model (1) are identifiable (Kurkalova, Kling, and Zhao, 2006). If the farmer has already adopted CT, the expected net returns from CT are greater or equal to those from conventional tillage plus the premium. Therefore, once the model parameters are estimated, the minimum subsidy needed to induce CT adoption for present non-adopters can be predicted as the difference between the expected net returns to conventional and conservation tillage, plus the premium, i.e., as $S = NR - \hat{\alpha}'\mathbf{w} + \hat{\gamma}'\mathbf{z}$. Here a “hat” over a parameter indicates the estimated value of the parameter.

To simplify the notation, denote

$$(2) \quad \boldsymbol{\beta}' = \left(\frac{1}{\sigma_\eta} \boldsymbol{\alpha}', \frac{1}{\sigma_\eta} \boldsymbol{\gamma}', \frac{1}{\sigma_\eta} \right), \quad \mathbf{x} = \begin{pmatrix} \mathbf{w} \\ \mathbf{z} \\ NR \end{pmatrix}.$$

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

$$(3) \quad \Pr(Y=1) = \Pr(\eta \leq \boldsymbol{\beta}'\mathbf{x}).$$

If a sample of farm-level data on both the adoption of CT, Y , and the explanatory variables, \mathbf{x} , is available, model (2) parameters, $\boldsymbol{\beta}$, are estimable using the standard Logit model techniques.

The next section presents a modification of model (2) 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 farmers indexed by i , each farming a_i acres, and each making the decision on the use of CT independently of the other farmers. Let $Y_i = 1$ if the farmer chooses to use CT on the farm and $Y_i = 0$ if he/she chooses conventional tillage, and let the choice of CT for

each farmer be governed by model (3). The grouped dependent variable logistic (GDVL) model (Wade 2011) assumes that the individual acres farmed, a_i , are known to the researchers, but the individual CT choices, Y_i , are not observed by the researchers. Instead, the sample of farmers is divided into J distinct groups G_j indexed by j , each containing N_j farmers, so that

$$\sum_{i \in G_j} i = N_j, \quad \sum_{j=1}^J N_j = N, \quad \text{and the researchers observe the estimates of the shares of acres in CT}$$

for each group j . The estimates of the shares of acres in CT for each group are assumed to be the

$$\text{acres-weighted expected values of the group-average individual choice variables, } \frac{1}{\sum_{i \in G_j} a_i} \sum_{i \in G_j} a_i Y_i,$$

subject to the Normal errors, with the latter distributed identically and independently across the groups. That is,

$$(4) \quad p_j = \frac{1}{\sum_{i \in G_j} a_i} \sum_{i \in G_j} \frac{a_i \exp(\boldsymbol{\beta}' \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}' \mathbf{x}_i)} + \varepsilon_j, \quad \varepsilon_j \sim N(0, \sigma_\varepsilon)$$

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

The probability model (4) leads to the following likelihood for the j^{th} group of observations

$$(5) \quad L(\boldsymbol{\beta}, \sigma_\varepsilon | p_j, \mathbf{x}_i (i \in G_j)) = -\frac{1}{2} \ln(2\pi\sigma_\varepsilon^2) - \frac{1}{2\sigma_\varepsilon^2} \left\{ p_j - \frac{1}{\sum_{i \in G_j} a_i} \sum_{i \in G_j} \frac{a_i \exp(\boldsymbol{\beta}' \mathbf{x}_i)}{1 + \exp(\boldsymbol{\beta}' \mathbf{x}_i)} \right\}^2.$$

To estimate the parameters of interest, $\boldsymbol{\beta}$, σ_ε , we apply the method of maximum likelihood based on the equation (5) to the data described in the next section.

Data Description and Variable Construction

We study the CT adoption by Iowa corn and soybean producers. We model the decision on tillage on a field scale. In econometric estimation, we supplement the field-scale data on cropping patterns and physical characteristics of the land, with less spatially detailed measures of climatic and farm characteristics. Most importantly, the dependent variable is the county-average rate of CT adoption.

The empirical study of the state of Iowa's corn and soybean production combines the CT use data from the Conservation Technology Information Center (CTIC) National Crop Residue Management Survey (NCRMS) (CTIC 2012), the cropping pattern data developed from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) remote sensing crop cover maps (USDA-NASS 2010), the soils characteristics data from Iowa Soil Properties and Interpretations Database 7.0 (ISU 2004), the climatic data from the National Climatic Data Center (NCDC, 2010), and the farm indicators from the 2002 Census of Agriculture (USDA-NASS 2004). The presentation below provides the description of the dependent variable sources followed by the justification and construction of the independent variables.

Tillage adoption / dependent variable data

The NCRMS is the only consistent nation-wide survey of county-average CT use that has been running annually from 1989 to 1998, and biannually from 1998 to 2004.¹ We use the two latest years of Iowa data available, that for 2002 and 2004. The CTIC records are based on the roadside

¹ Other recent data on the use of CT have been reported at even higher level of aggregation such as a state (Horowitz, Ebel and Ueda, 2010) or a multi-state (large watershed) level (USDA-NRCS, 2010, 2011).

transect method that requests county conservation experts to drive a set course through the county to visually assess the use of CT at half-mile or mile intervals (CTIC 2012). Any field that maintains 30% or more of crop residue after planting is considered to utilize CT practices. The per county proportion of the CT acres relative to the total acres for each crop, corn and soybeans, is used as the dependent variable in the study.

Independent variable data

The finest geographical scale independent variable data, the indicators of the current and previous year's crops grown, come from the 2002 and 2004 USDA NASS remote sensing crop cover maps using a 400m by 400m resolution (approximately 39 square acres) (USDA-NASS 2010). The study focuses on corn and soybean production and consequently omits all fields that harvest other crops.² The rotations being considered are therefore, corn following corn (CC), corn following soybeans (CS) and soybeans following corn (SC). These sequences cover the majority of Iowa cropland (Stern et al. 2008; Horowitz, Ebel and Ueda 2010).

In the case of soybeans, an unusual 8% of the sample is showing soybeans following soybeans³. Due to the problems with *Heterodera glycines* (Workneh et al. 1999), pod rot and sudden death (Baird et al. 1997), among other diseases associated with this rotation, it is an unlikely choice for Iowa farmers seeking to maximize profits. This overestimation of soybeans following soybeans is corrected by reassigning those fields to SC (Kurkalova, Secchi and Gassman 2010; Secchi et al. 2011). While the corn monoculture may historically be unusual,

² Land-use data pertaining to crop rotations are available for several years and while the historical management practices may be useful in understanding tillage adoption this leaves too many combinations of Iowa crops to be considered—Stern, Doraiswamy, and Akhmedov (2008) discovered 128 possible crop combinations in a 7 year period.

³ Using 1979-2003 Iowa data Hennessy (2006) also did not find any corn producing fields that produced two consecutive years of soybeans in a four year rotation.

ethanol and the new demand for corn (Marland et al. 2001; Triplett and Dick 2008; Nassauer et al. 2011) may change the previous dynamic of equal corn to soybeans acres to one that produces more corn than soybeans (Duffy and Correll 2006; Malcolm and Aillery 2009). More acres may also be placed in continuous corn due to perceived improvements in hybrid seeds, high corn prices and favorable weather conditions (Duffy and Correll 2006; Shaw et al. 2012). Thus CC rotations are retained as a measure of this recent shifting of soybean fields to corn (Stern et al. 2008). The final two year sample has 123,157 observations (with average field size of 303 acres) of which 15% is in CC, 39% in CS and 46% in SC.

The analysis focuses on rotated fields versus non-rotated fields i.e. the estimates for *CS* and *SC* are given relative to *CC*. Although Fuglie (1999) found that crop rotation has an insignificant effect on CT adoption, there is sufficient evidence that rotation choice does affect CT success in that it introduces crop diversity which helps with weed management (Hill 2000; Shaw et al. 2012). Therefore, the prediction here is that relative to *CC*, *CS* and *SC* will have a positive effect on CT adoption and further predict that the magnitude of *SC* will supersede that of *CS*. This is due to tillage choice having little effect on soybean yields (Al-Kaisi and Hanna 2009, 2010), evidence of more no-tillage systems already being applied more heavily to soybean fields (Hill 2001; Young 2006), problems with giant ragweed identified with corn fields (Gibson, Johnson and Hillger 2006) and most importantly, no-tillage having greater economic returns for soybeans than other tillage systems (Yin and Al-Kaisi 2004).

Expected net returns to conventional tillage.

In this profit maximizing model the expected net returns to conventional tillage (NR) are vital to estimating the monetary incentives to switch to CT methods. Here it is used in two ways, as a

proxy for farm income and in this empirical setting its coefficient estimate represents the inverse of the logistic error multiplier, $1/\sigma_\eta$ (see Cameron (1988)). These data are thought to be known to the agents but are unavailable to researchers. Its importance to the model necessitates having a good approximation of individual net returns; therefore these data are calculated using field yield, cost and price as the three major components. We assume that the prices and costs are homogeneous across the state and use NASS estimates as their input values.⁴ Consequently, the distribution of NR is driven by the distribution of the expected yields.

While reliable county level yield data are readily available, this aggregation provides a poor representation of field level variability (Claassen and Just 2011) and since the NR data relies heavily on yield data we prefer to calculate the field level yield thereby capturing the intra-county heterogeneity. This is done by following the procedure in Secchi et al. (2009) which assumes that farmers have enough experience to maximize the yield on their fields and estimates the potential yield as the product of the corn suitability rating (CSR) and a crop yield coefficient, α : $yield_{ic} = CSR_{ic} \times \alpha_{mc}$, where subscript i ($i = 1 \dots n$) indexes fields in a given county, subscript m ($m = 1 \dots M$) indexes counties and c indicates the crop. The problem however is that α_{mc} is also unknown. Notice that α_{mc} does not vary within each county, therefore additional computations are needed to estimate field level yield. If one considers the average county yield, avg_yield , to be weighted by acres the yield multiplier becomes

$$(6) \quad \alpha_{mc} = avg_yield_{mc} \cdot \sum_{i=1}^n acres_{ic} / \left(\sum_{i=1}^n CSR_{ic} \times acres_{ic} \right).$$

⁴ The cost formula is an adaptation of the Duffy and Smith (2002; 2004) production budgets and is calculated as a linear function of machinery, seed, chemical, interest on pre-harvest costs, labor and crop insurance costs.

Equation (6) is calculated using state extension county average yield data (see Johanns (2011a; 2011b)) and the soil database's field acres and CSR values. NR is then the difference between the revenue received and the cost.

Farm operator and farm characteristics.

Farm operator characteristics available at the county level from the 2002 Census of Agriculture (2004) are used to estimate the premium. Since this census is a farm mandatory survey one can assume that the statistics provided are representative of the state of Iowa. With that said, the statistics are for all farm types in the county. A major challenge is that it is impossible to independently tease out the statistics related to soybeans or corn producers from these publications. For example, if one is interested in utilizing the average age as an explanatory variable, he/she must use the average age of farmers for all farm types, as there is no option that allows for query into the average age of corn farmers.

Two widely used operator characteristics examined in conservation research are gender and farm experience. While the literature thus far suggests that women are more sensitive to environmental concerns (Rogers and Vandeman 1993; Corselius, Simmons and Flora 2003) the economic literature on conservation practices indicates that men are more likely than women to adopt CT (see Rogers and Vandeman (1993) and Kurkalova et al. (2006)) . The same positive response to the *MALE* gender effect is expected here. *AGE* is used as a proxy for experience. The theory that an older or more experienced farmer is more likely to utilize CT mechanisms has been wildly tested with varying results: it is found to have a positive, negative and insignificant effect by different studies (Kurkalova et al. 2006; Knowler and Bradshaw 2007). However, given

that the literature suggests that over time, with more experience CT use will increase (Uri 1999b; Al-Kaisi and Yin 2004), *AGE* is expected to positively influence the adoption decision.

Land tenure is thought to increase the likelihood of healthy soil practices (Knowler and Bradshaw 2007; Davey and Furtan 2008) and therefore, increase the probability of using conservation systems. However, several studies found that this is not the case (see Fuglie (1999), Soule et al. (2000) and Kurkalova et al. (2006)). Claassen and Morehart (2009) on the other hand, suggests that ownership allows farmers to position themselves to enter into conservation programs more so than non-owners. This finding, coupled with the significant results found when *TENANT* was used in the 1997 CTIC application of the GDVL model gives us cause to further explore this characteristic. It is expected to have a negative effect on CT adoption.

Contrary to some studies suggestions that the organizational structure has no significant effect on predicting conservation behavior (Napier and Tucker 2001), this research postulates that organization type may influence management decisions. Given evidence that nonfamily organizations have little bearing on the adoption decision (Lee and Stewart 1983) we opt to narrow our analysis of the organizational structure's effect and explore the effect that family organizations have on tillage adoption. The organizational types investigated are therefore, family corporations (*CORP*) and family farms (*FAMILY*)⁵. If different types of organizations have differences in types of expenditures, access to loans, or have different types of leasing and tenure arrangements, they may choose different soil management systems or may find it arduous to switch to different mechanisms. Like Lambert, Sullivan, and Claassen (2007) we expect family organizations to have a positive effect on adoption, and like results found in Davey and Furtan (2008), *CORP* is expected to have a greater effect on the adoption of CT than *FAMILY*.

⁵ Partnership's effect on tillage adoption was considered as a regressor however, the available data does have separate family and non-family partnership statistics. We therefore opt to omit partnerships from the analysis.

Climate variables.

The climate data are the NCDC (2010) daily precipitation, maximum temperature and minimum temperature measurements taken over the corn growing season for years 1970-2004. The growing season dates used are the mid-date in the range of the most active corn planting period and the mid-date in the range of the most active corn harvesting period, May 10-October 23⁶ (USDA, NASS 2010). Constructing the climate regressors in this manner captures their within-season and cross-seasonal variations.

To associate the climatic variable measurements with fields, the majority of the fields are assigned to the weather stations that are physically the closest, and the rest of the fields are assigned to a station that is in the same county though it is unknown whether the station is indeed physically the closest. There are therefore 162 weather stations used in the study. This is a minor discrepancy in the assignment of fields to stations that should not manifest in the results. All weather stations used have at least one half of the growing season daily observations available. The economic model utilizes climate variables in two ways, to contribute to the estimation of the net returns to CT and to model the adoption premium.

The climate regressors used in the estimation of the net returns to CT are the means of the temperature and precipitation (*TMAX*, *TMIN* and *PRCP*) for this 35 year period. Long-run weather variables such as these have been used with mixed results: Kurkalova et al. (2006) shows positive and insignificant results for average precipitation, negative and significant results for minimum temperature and positive and significant results for maximum temperature; Ding et al. (2009) shows negative and insignificant results for precipitation, and positive insignificant

⁶ There are only 10 days between the corn and soybeans growing season so we opt to use only the corn growing season dates.

results for average temperature; Soule et al. (2000) shows a negative effect for precipitation and temperature. With this said, the general consensus is that CT does not perform well on cold wet soil (Soule et al. 2000). Fields with more crop residue will be better apt at retaining soil moisture and will therefore require less precipitation than fields with less crop residue (Uri 2000a) making CT beneficial to fields that experience dryer, warmer weather. *PRCP* is therefore expected to have a negative effect on the adoption of CT, and *TMAX* and *TMIN* are expected to have positive effects.

The variance of daily precipitation, σ_{prcp}^2 , is calculated using the daily rainfall totals from the same 35 year period. The rationale for the development of σ_{prcp}^2 is the sensitivity of crop yields to weather variability—precipitation in particular—which in turn affects the variability of the CT payoff.

Natural resource characteristics.

Soil conditions are other important factors when choosing tillage mechanisms (Al-Kaisi and Hanna 2010). The soil conditions considered are land slope, drainage in the form of permeability and frequency of floods. Resource and soil characteristics such as HEL (highly erodible land) are also important components to the tillage preference. It is well known that land classified as HEL is oftentimes placed in conservation programs or is subject to conservation compliance that mandates the use of conservation practices to maintain eligibility for government payments (Secchi et al. 2009). Therefore HEL status positively affects the adoption of CT. And while this variable is available in the ISPAID database, 1466 observations (or 97,771 acres) are not assigned a HEL category. Hence, land slope (another widely used variable see Fuglie and Bosch (1995), Kurkalova et al. (2006), Kurkalova and Rabotyagov (2006), Knowler and Bradshaw

(2007), Huang et al. (2008) and Sheeder and Lynne (2011)) is used as a proxy for HEL. *SLOPE* here is the average of the lowest and highest range of the incline of the soil surface (IASU 2004). This variable's high colinearity with HEL (correlation coefficient of 0.8) and the retention of the observations makes it a favorable choice.

Precipitation shocks such as drought and flood may also affect tillage choice. Ding et al. (2009) indicates that farmers who have experienced several years of drought are more likely to use no-till than those who have not. This is consistent with aforementioned conditions under which CT performs well. *FLOOD* is used in an attempt to capture the effect of precipitation shocks. This indicator variable describes how often soil is temporarily covered with water from overflowing streams and runoff from adjacent slopes (IASU 2004). It is indexed from 0 to 50 (from no flooding to ponded) and is therefore expected to impede CT adoption.

Well drained soil is important when using CT (Triplett and Dick 2008; Al-Kaisi and Hanna 2010) and soil permeability, *PERM*, is used to capture this effect. Because of the residue cover on land that is in CT, less permeable soil will have the potential to get waterlogged. To this point, De La Torre Ugarte et al. (2004) has found that incentive payments to fields with well drained soils are lower than those made to poorly drained soils. *PERM* ranges from 0 to 90 for high to low permeability, and is therefore predicted to have a negative coefficient estimate.

The variables described above are what we believe to be the attributes of the three components of the economic model: $\alpha'w \geq NR + \gamma'z$. The probability of adoption is then modeled using equation (3) which is applied to the likelihood function (5). Their coefficient estimates are then used to calculate field level subsidies. How these components correspond to the economic model of adoption is demonstrated below:

$$(7) \quad \alpha'w = \alpha_1 CS + \alpha_2 SC + \alpha_3 SLOPE + \alpha_4 PRCP \\ + \alpha_5 TMAX + \alpha_6 TMIN + \alpha_7 PERM + \alpha_8 FLOOD$$

$$\begin{aligned}
\boldsymbol{\gamma}'\mathbf{z} = \sigma_{pre}^2 & \left[\gamma_1 \cdot AGE \cdot CC + \gamma_2 \cdot AGE \cdot CS + \gamma_3 \cdot AGE \cdot SC \right. \\
& + \gamma_4 \cdot MALE \cdot CC + \gamma_5 \cdot MALE \cdot CS + \gamma_6 \cdot MALE \cdot SC \\
(8) \quad & + \gamma_7 \cdot NR \cdot CC + \gamma_8 \cdot NR \cdot CS + \gamma_9 \cdot NR \cdot SC \\
& + \gamma_{10} \cdot CORP \cdot CC + \gamma_{11} \cdot CORP \cdot CS + \gamma_{12} \cdot CORP \cdot SC \\
& + \gamma_{13} \cdot FAMILY \cdot CC + \gamma_{14} \cdot FAMILY \cdot CS + \gamma_{15} \cdot FAMILY \cdot SC \\
& \left. + \gamma_{16} \cdot TENANT \cdot CC + \gamma_{17} \cdot TENANT \cdot CS + \gamma_{18} \cdot TENANT \cdot SC \right]
\end{aligned}$$

The estimated model is therefore given by general specification shown in model (4). We have $J = 594$ year-county-rotation groups in the pooled 2002 and 2004 sample (i.e. $2 \times 99 \times 3$), and $N = 123,157$ is the total number of observations each representing a field where an agent made a choice between CT and conventional tillage.

Results and discussion.

Table 2 displays regression results from the model (4). The estimates presented are of $\boldsymbol{\beta}$ (note $\boldsymbol{\beta}' = (\boldsymbol{\alpha}'/\sigma_{\eta}, \boldsymbol{\gamma}'/\sigma_{\eta}, 1/\sigma_{\eta})$), which are used to predict the effect the variable has on the likelihood of CT adoption. The discussion of results therefore keeps both the probability of adoption and its effect on the subsidies in mind. As indicated in equation (7), the contributions to the net returns to CT are those regressors *not* interacted with σ_{pre}^2 . The reader may interpret a positive result as increasing the likelihood of adoption while decreasing the incentive payments and a negative result as decreasing the likelihood of adoption while increasing the incentive payments. For the contributions to the premium (the regressors are interacted with σ_{pre}^2 as seen in equation (8)), the reader may interpret a negative response as increasing the likelihood to adopt while decreasing the adoption premium and a positive result as decreasing the likelihood of adoption while increasing the premium. Overall the model performed well. It shows robust results, with

74% of the variable estimates corresponding with predictions given in the previous section, and with 59% significant at the 10% level or lower.

First we examine the net returns to CT. Coefficient estimates for *SC*, *SLOPE*, *PRCP*, *TMAX*, *PERM* and *FLOOD* all performed as predicted with regards to direction and statistical significance with *PRCP* having the largest effect. This result is in keeping with the consensus that CT does not operate well under damp conditions and except for *SLOPE* are very similar to results in Wu et al. (2004). The two variables that did not perform as expected are the dummy for CS rotations and the average minimum daily temperature.

The CS dummy's small and statistically insignificant effect is an indication that adoption may not depend on rotation. Rather it is the crop grown, soil properties and precipitation levels that dictates which tillage mechanism is used. If in fact farmers no longer perceive a yield lag from planting CC, due to increased nitrogen use or other reasons, (Duffy and Correll 2006; Hennessy 2006) they may farm corn more intensively, exacerbating the weed problem (see Gibson et al. (2006) and Shaw et al. (2012)) hence making conventional tillage systems more attractive. Evidence of this lack of yield lag is seen in table 3 with both CC and CS averaging 155 bu/acre for the two year period. This result may also be a case of poor data availability. The CTIC average adoption rates are only available by crop and tillage type, and as such there is no adoption average based on rotations, i.e. identical adoption rates are used for CC and CS fields in the same county. The regressions may then be unable to find significant differences between the two systems.

The premium predictors are the 2002 Census of Agriculture variables interacted with crop rotation dummies and σ_{prcp}^2 . These interaction terms are found to be highly collinear; however, the inclusion of σ_{prcp}^2 is imperative to estimating agents' potential risk and is therefore

included despite its statistical effect on the individual components of the premium specification. Also, since the ML estimates are consistent (Cameron and Trivedi 2005; Wooldridge 2009) the high standard errors are only of concern when conducting hypothesis tests and should still yield reliable subsidy estimates.

We find the experience proxy to be as predicted but the gender effect to be opposite to our expectation. *AGE*'s negative effect on the premium lends credence to the theory that more experienced farmers are more likely to use conservation mechanisms (Rahm and Huffman 1984; Gould, Saupe and Kleeme 1989). Contrary to our earlier predictions, but similar to results found in Davey and Furtan (2008), *MALE* has a negative and significant effect on CT adoption. Male farmers (which represent over 90% of Iowa farmers, see table 1) may behave differently if there are environmental stressors (or other latent variables) which unfortunately cannot be captured by our temporal climate variables. For example, in April 2002 (the month before planting), the state experienced dramatic variations in temperature, extreme weather events and up to 5.5 inches of precipitation in some regions (Iowa Department of Agriculture). The effects of these shocks are lost in the aggregation process. These events could affect farmers' perceptions of the impending weather, creating uncertainty which may entice them to use conventional tillage mechanisms.

The results indicate that the organizational type does play into the tillage decision. The estimates are generally as predicted with *CORP* having a stronger effect than *FAMILY*. The organizational structure however, may be capturing the size effect. The size of the farm may affect tillage decisions in that larger farms are more likely to adopt new technologies than smaller farms (Westra and Olson 1997; Fuglie 1999; Soule et al. 2000; Fuglie and Kascak 2001; Davey and Furtan 2008) and explore more land-use options (Lambert et al. 2006). The idea being that small farms pose more of a financial risk and have high per acre costs makes it

difficult to acquire new technologies and impedes CT adoption (Lee and Stewart 1983; Lambert, Sullivan and Claassen 2007). In general, 20% of family or individual farms and 58% of family-held corporations are 500 to 999 acres or more (USDA, NASS 2004). Larger farms may also have the resources to invest in expensive CT equipment while the opportunity cost for smaller farms may be too great. It is difficult to separate organizational structure from size because of their high collinearity but it would be interesting to see empirically what effects each has on tillage adoption. If, as we postulate, size and organizational type have similar effects on CT adoption, small farms need greater incentives to switch to CT than larger farms.

The *NR* interactions are used as proxies for risks associated with farm income and are found to be negative and highly significant. This is not surprising since profitability is of most importance when choosing tillage mechanisms (Napier and Tucker 2001) and if risks associated with those profits are high farmers may invest in other methods such as CT. It is clear from the results that as *NR* risks increase the probability of adoption increases. Except for *NR*, soybean interactions in the premium are much smaller in absolute value relative to their corn counterparts and are statistically insignificant. This as well as the strong positive effect of *SC* relative to *CC*, is an indication that soybean producers have little effect on the adoption premium and is consistent with the soybean subsidies discussed below.

Using the estimation results from table 2 and the model for the subsidies, $S = NR - \hat{\alpha}'\mathbf{w} + \hat{\gamma}'\mathbf{z}$, we predict field level subsidies showing a sample average incentive of \$29.85/acre (standard deviation \$35.68) for *CC*, \$28.62/acre (standard deviation \$32.84) for *CS* and \$4.19/acre (standard deviation \$16.61) for *SC*. It is not surprising that *SC* subsidies are the lowest of the three rotations when one considers that soybean yields are unaffected by tillage mechanisms (Al-Kaisi and Hanna 2010) and therefore choosing CT would lower cost without

affecting yields (Yin and Al-Kaisi 2004). The large standard deviations are also not surprising since we know several fields already use the new practice (see table 3). For corn fields, CT advocates would hope CT acres are more evenly distributed between corn and soybean fields. Both CT averages in table 3 and average subsidy estimates suggest that this is not the case. While this sample has shown an overall increase in CT over the 2 years, it seems there has been a switch in proportion of CT acres from corn to soybeans. This is unfortunate because while this sample shows an increase in cropland, more comprehensive studies show soybean acres declining (see Stern et al. (2008)). Since most of Iowa cropland is in corn and soybeans, this is crude evidence that there is little application of continuous CT.

The relatively small differences between *CS* and *CC* effects are clearly reflected by the subsidy estimates: the subsidies for *CC* are almost identical to those for *CS*. The high corn acres are most likely due to recent high corn prices (Secchi and Babcock 2007; Leatherman, Peterson and Smith 2007) and the high subsidies may be due to CT yield uncertainty caused by either weather variability in the month prior to planting or long-term precipitation variability indicated by the large σ_{prec}^2 (see table 1). It may also be the case that the literature has underestimated farmers' perceptions of the ragweed problem associated with corn fields.

The county average subsidy estimates for each crop are illustrated in figure 1 and figure 2. The results here are similar to those found in Kurkalova and Kling (2002) in that it is more costly to implement CT in areas with high productivity and cooler climate. When one compares the corn map (figure 1) with the soybeans map (figure 2) there are a few inconsistencies. One would expect a farm that charges high prices for the adoption of CT corn acres to charge relatively high prices for soybean acres. However, there are a few counties where we find that this is not the case. On average, these farms seem to require relatively high payments for corn

and relatively low payments for soybeans and vice versa. This unexpected result could also be a result of aggregating the field level subsidies.

This study estimates average subsidies for corn and soybean farmers to be \$18/acre which is akin to subsidies estimated by studies like Kurkalova et al. (2006) and De La Torre Ugarte (2004)⁷. Furthermore, it finds that 5% of CC, 12% of CS and 41% of SC fields are willing to accept no payments for using CT. This is an outcome of the model's ability to deconstruct the CTIC county average adoption rates. It is clear that the sample average is dramatically affected by the low incentives recommended for soybean fields. There clearly needs to be more insight into factors that affect corn agents' choices. Econometric analysis of this may be challenging using this model however, since isolating corn fields leaves the researcher with a low sample adoption rate, which in turn makes this model and other logistic models difficult to estimate.

One unique feature of this method is the ability to quantify both the deviations in the logistic and the normal errors. Even in this large dataset the estimate of $\sigma = 0.18$ is large and significant. Kurkalova and Wade (2011) Monte Carlo simulations indicate that large error is clearly echoed in the results and special care should be taken in model specification. We estimate the standard deviation of the logistic error as $\sigma_{\eta} = 32.9$ (standard error 13.7). This estimate is much smaller than previous estimates of this error using earlier data (see Kurkalova and Rabotyagov (2006)) which may be evidence of well constructed NR data. While this relatively small estimate may be attributed to the division of the statistical noise across the two errors, the large standard error may bring into question the robustness of the results.

⁷ Several specifications were explored for regression estimation all yielding the same average subsidy estimates. That the subsidy recommendations do not vary widely among model specifications demonstrates the robustness of the model and legitimizes the theory behind variable choice.

The reader should note that the subsidy estimates are based on soil properties, climate factors and farmer risk. Neither the net returns to conventional tillage nor CT incorporate payments that farms may already receive. It is therefore possible that the CTIC data includes acres on which farms are already receiving payments. A \$0 subsidy may therefore be a result of payments already being received for CT or some other practice for which CT is a result.

Conclusions

This study focuses on incentive payments necessary to make CT fiscally attractive to non-adopters, and uses micro-level (or field-level) choice determinants and the corresponding county proportion of acres in CT. The modeling strategy allows full recovery of the logit probabilities of the adoption of CT even though the information on the adoption is available only as aggregated data over counties and crops. Since the standard logit cannot be utilized we implement the GDVL method in estimation of the cost of CT adoption. GDVL method lends itself nicely to CTIC data as it reports the CT use by county. The model interprets the county average proportion of land in CT as an expected value of CT adoption and unlike previous studies that aggregate the characteristics, then conduct analysis on the group (see Miller and Plantinga (1999)), this study uses all of the individual attributes available in hopes of mitigating the individual-level information lost in the aggregation process (Schuessler 1999) analyzing marginal effects of discrete predictor variables, and improving statistical significance (Claassen and Just 2011).

If farms focus on profit maximization and do not typically consider social impact when making management decisions (Uri 1998) policymakers' challenge is to mitigate negative farm externalities while maintaining their profitability. Minimizing the payments that are used to

incentivize environmentally friendly and sustainable agriculture is also in the public's best interest, and one way to do this is through developing policies that incorporate individual farm or field characteristics and not assume homogeneity across broad geographic regions. This analysis is based on micro-level data even when the data on choices are only available on an aggregate basis. This model provides a tool for inexpensive state or county wide policy analysis as opposed to more general regional or county wide policy. Policymakers may be able to empirically estimate the within county effect of taxes on fertilizer use or unhealthy fertilizer application techniques without the use of expensive surveys.

We estimate a sample average CT adoption subsidy of \$18/acre for Iowa corn and soybean producers. This estimate results from the CTIC 2002 and 2004 farm management data which makes it one of the most recent predictions of the cost to switch to benign farm practices. The results tell a clear and consistent story of factors affecting CT which coincide with present theories on how climate, farm and soil conditions affect tillage decisions. Soybean fields are shown to have a large positive effect on CT adoption which is consistent with the small and insignificant affect it has on the adoption premium as well as our knowledge that a large percentage of soybean fields are already using the new practice due to its profitability and increasing use of glyphosate-resistant soybean seeds (Young 2006; Shaw et al. 2012). The small subsidy recommendations for soybean fields (relative to corn fields) therefore come as no surprise. We also find that more experienced agents as well as the type of operation play positive and significant roles in soil conservation investments. That the regression is unable to tease out the rotation effect on tillage choice is unfortunate, given the interest in using rotation as a means to promote sustainable agriculture (Hennessy 2006). The simultaneous increase in CT usage and

corn acres makes one think that the two are correlated. However, our study could make no conclusions based on regression analysis of the available data.

Effective subsidies must be competitive with market prices and maintained over time or farmers will withdraw fields (Hill 2001; Napier and Tucker 2001); unfortunately, those agents who have strong economic goals may simply not buy into conservation programs (Sheeder and Lynne 2011). Also as corn prices and productivity increase (Secchi et al. 2008; Elmore and Taylor 2011), the subsidies needed to achieve these goals will be increasingly costly (Smith et al. 2007). A better understanding of the drivers of CT adoption will be ever more imperative.

Table 1. Variable Descriptions and Summary Statistics for Pooled Dataset

Name	Description	Units	Mean	SD
<i>Adopt CT</i>	The county average proportion of corn or soybean acres in conservation tillage	Number	0.588	0.258
<i>CC</i>	1-Corn following corn rotation; 0-Otherwise	Number	0.228	0.420
<i>CS</i>	1-Corn following soybeans rotation; 0-Otherwise	Number	0.306	0.461
<i>SC</i>	1-Soybeans following corn rotation; 0-Otherwise	Number	0.465	0.499
<i>PRCP</i>	Mean of daily precipitation during the corn growing season	Inches	0.124	0.009
<i>TMAX</i>	Mean of daily maximum temperature during the corn growing season	Fahrenheit	77.9	1.5
<i>TMIN</i>	Mean of daily minimum temperature during the corn growing season	Fahrenheit	55.1	1.7
σ_{prcp}^2	Variance of daily precipitation during the corn growing season	Inches ²	0.133	0.017
<i>SLOPE</i>	Land slope	Percentage	5.007	5.078
<i>PERM</i>	Soil permeability (discrete variable)	Number	49.8	16.9
<i>FLOOD</i>	Flood frequency (discrete variable)	Number	5.02	11.58
<i>AGE</i>	County average farm operator age	Years	54.3	1.6
<i>MALE</i>	Proportion of male operators to the total number of farm operators in the county	Number	0.932	0.026
<i>TENANT</i>	Proportion of farms operated by tenants to the total county farms	Number	0.121	0.041

<i>CORP</i>	Proportion of farms operating as family-held corporations to the total county farms	Number	0.058	0.025
<i>FAMILY</i>	Proportion of family or individual farms to the total county farms	Number	0.865	0.033
<i>NR</i>	Expected net returns to conventional tillage	\$/ acre	108	101

Table 2. ML Estimates of the GDVL Model Using Pooled CTIC Tillage Data

Variables	Coefficients, β	Estimates
<i>CS</i>	β_1	1.30 (1.17)
<i>SC</i>	β_2	4.82 (1.31)***
<i>SLOPE</i>	β_3	0.263 (0.049)***
<i>PRCP</i>	β_4	-20.0 (10.0)**
<i>TMAX</i>	β_5	0.079 (0.046)*
<i>TMIN</i>	β_6	-0.044 (0.056)
<i>PERM</i>	β_7	-0.0264 (0.0072)***
<i>FLOOD</i>	β_8	-0.074 (0.024)***
$\sigma_{prcp}^2 \cdot AGE \cdot CC$	β_9	-0.56 (0.33)*
$\sigma_{prcp}^2 \cdot AGE \cdot CS$	β_{10}	-0.56 (0.34)*
$\sigma_{prcp}^2 \cdot AGE \cdot SC$	β_{11}	-0.27 (0.35)
$\sigma_{prcp}^2 \cdot MALE \cdot CC$	β_{12}	82.4 (23.2)***
$\sigma_{prcp}^2 \cdot MALE \cdot CS$	β_{13}	75.8 (23.0)***
$\sigma_{prcp}^2 \cdot MALE \cdot SC$	β_{14}	24.7 (26.7)
$\sigma_{prcp}^2 \cdot NR \cdot CC$	β_{15}	-0.203 (0.091)**
$\sigma_{prcp}^2 \cdot NR \cdot CS$	β_{16}	-0.185 (0.091)**
$\sigma_{prcp}^2 \cdot NR \cdot SC$	β_{17}	-0.238 (0.093)**
$\sigma_{prcp}^2 \cdot CORP \cdot CC$	β_{18}	-110.0 (42.9)**
$\sigma_{prcp}^2 \cdot CORP \cdot CS$	β_{19}	-84.5 (41.5)**

$\sigma_{prep}^2 \cdot CORP \cdot SC$	β_{20}	-28.7 (49.0)
$\sigma_{prep}^2 \cdot FAMILY \cdot CC$	β_{21}	-37.5 (24.7)
$\sigma_{prep}^2 \cdot FAMILY \cdot CS$	β_{22}	-25.9 (24.6)
$\sigma_{prep}^2 \cdot FAMILY \cdot SC$	β_{23}	25.5 (31.2)
$\sigma_{prep}^2 \cdot TENANT \cdot CC$	β_{24}	-23.7 (22.0)
$\sigma_{prep}^2 \cdot TENANT \cdot CS$	β_{25}	-15.8 (21.5)
$\sigma_{prep}^2 \cdot TENANT \cdot SC$	β_{26}	25.1 (22.7)
<i>NR</i>	$1/\sigma_{\eta}$	0.030 (0.013)**
σ		0.175 (0.005)***
<i>LL</i>		191.298

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<.01

Table 3. Average Yield, CTIC Adoption of CT and Acres for 2002 and 2004 Data

Rotation	Year	Yield (bu/acre)	Adopt CT	Acres (%)
CC	2002	148 (57)	0.405 (0.223)	15
	2004	161 (60)	0.390 (0.209)	15
CS	2002	147 (56)	0.413 (0.219)	40
	2004	163 (59)	0.407 (0.229)	38
SC	2002	43 (16)	0.707 (0.192)	45
	2004	44 (16)	0.805 (0.155)	47

Note: Standard deviations in parentheses

Table 4. Percentage of Acres Willing to Adopt CT within the Given Subsidy Ranges

Subsidy (S, \$/acre)	All	Corn	Soybeans
$S < 10$	62.5	37.9	91.6
$10 \leq S < 20$	6.6	10.5	1.9
$20 \leq S < 30$	7.4	12.3	1.5
$30 \leq S < 40$	7.1	12.2	0.9
$40 \leq S < 50$	4.8	8.1	0.9
$S \geq 50$	11.8	19	3.2

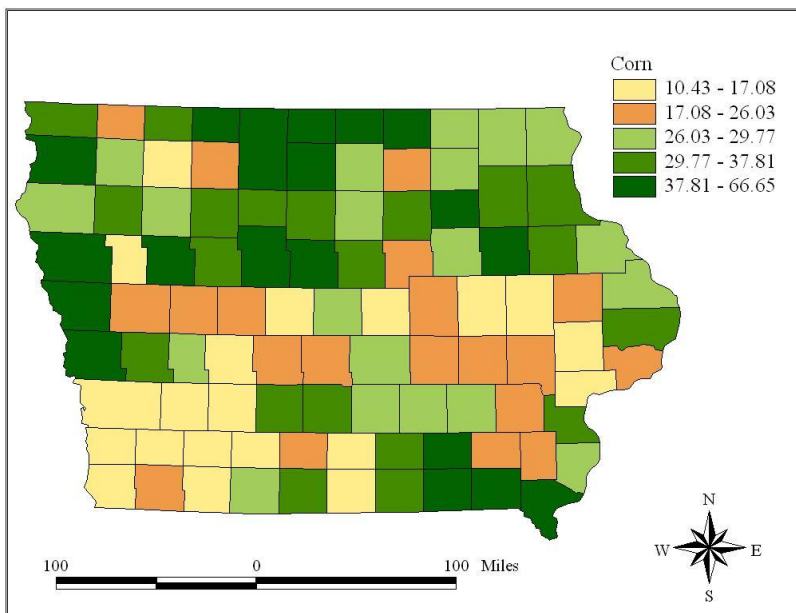


Figure 1. County Average Subsidies for Iowa 2002 and 2004 Corn Fields

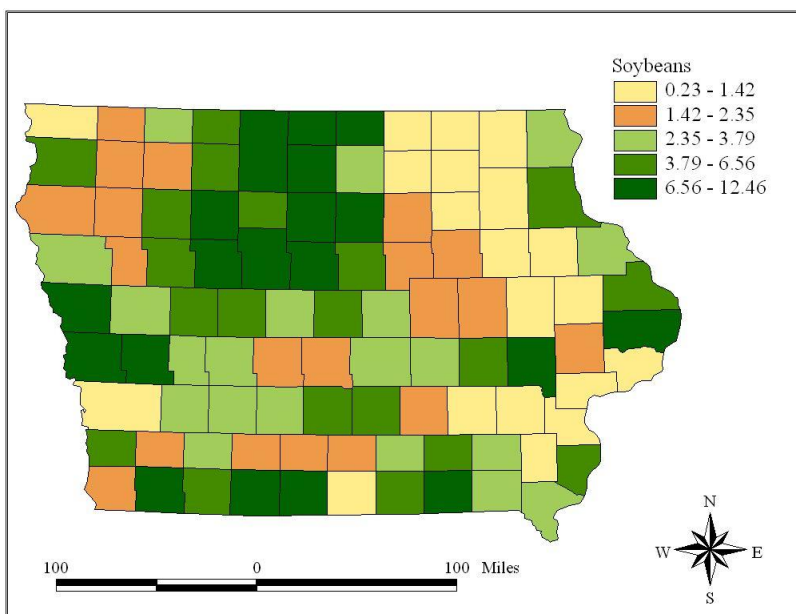


Figure 2. County Average Subsidies for Iowa 2002 and 2004 Soybeans Fields

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