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Conservation Tillage, Pesticide Use, and Biotech Crops in the U.S.A.

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Selected Paper prepared for presentation at the Agricultural and Applied Economics Association 2010 AAEA, CAES, & WAEA Joint Annual Meeting, Denver, Colorado, July 25-27, 2010

The views expressed are those of the authors and do not necessarily represent the views or policies of the U.S. Dept. of Agriculture or the U.S. Environmental Protection Agency

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Conservation Tillage, Pesticide Use and Biotech Crops in the U.S.A.

The environmental impact of conservation tillage (including no-till, ridge-till, and mulch-till) is well documented. By leaving substantial amounts of crop residue (at least 30 percent) covering the soil surface after planting, conservation tillage reduces soil erosion by wind and water, increases water retention, and reduces soil degradation and water and chemical runoff. In addition, conservation tillage reduces the carbon footprint of agriculture.

On the other hand, conservation tillage may increase pesticide usage, as farmers compensate for less tillage. As Fuglie (1999) notes, if pesticide use increases with conservation tillage, the environmental gains from reduced soil erosion may be offset by increased reliance on pesticides, which are a source of concern for their potential harm to human health and the environment. However, while studies of conservation tillage have clearly demonstrated significant environmental benefits from reduced soil erosion, much less is known about environmental costs and benefits from changes in pesticide use due to conservation tillage.

The use of conservation tillage practices was facilitated by the availability, since the 1980s, of postemergent herbicides that could be applied over a crop during the growing season. No-till had particularly benefited because weeds could be controlled after crop growth without tilling the soil. The use of herbicide-tolerant (HT) crops (particularly HT soybeans) has helped the continuation of that trend since it often allows a more effective and less costly weed control regime than using other post-emergent herbicides (Carpenter and Gianessi, 1999). By facilitating the use of conservation tillage (no-till in particular) the adoption of herbicide-tolerant crops may indirectly benefit the environment in the form of reduced soil losses and runoff. However, despite finding a strong association between the adoption of conservation tillage and the adoption of herbicide tolerant crops, a causal relationship has been difficult to demonstrate.

Adoption of conservation tillage by U.S. soybean growers has risen from about 30 percent from 1996 to 63 percent in 2006 (figure 1) while no-till (the most beneficial of the conservation till modes) has grown even more rapidly. Conservation tillage in corn fields has been a practice representing approximately a third of the corn acres in 1990 reaching about 40 percent in 2006.

U.S. farmers have adopted genetically engineered (GE) crops widely since their introduction in 1996. Soybeans and cotton genetically engineered with herbicide-tolerant traits have been the most widely and rapidly adopted GE crops in the U.S., followed by insect-resistant cotton and corn (Fernandez-Cornejo, 2009).

Herbicide-tolerant (HT) crops, developed to survive application of specific herbicides that previously would have destroyed the crop along with the targeted weeds, provide farmers with a broader variety of options for effective weed control. Based on USDA survey data, adoption of HT soybeans went from 17 percent of U.S. soybean acreage in 1997 to 68 percent in 2001 and 91 percent in 2007 (figure 2) and 2009. Plantings of HT cotton expanded from about 10 percent of U.S. acreage in 1997 to 56 percent in 2001 and 71 percent in 2009. The adoption of HT corn, which had been slower in previous years, has accelerated, reaching 68 percent of U.S. corn acreage in 2009.

Insect-resistant crops containing the gene from the soil bacterium Bt (*Bacillus thuringiensis*) have been available for corn and cotton since 1996. These bacteria produce a protein that is toxic to specific insects, protecting the plant over its entire life. Plantings of Bt corn grew from about 8 percent of U.S. corn acreage in 1997 to 26 percent in 1999, then fell to 19 percent in 2000 and 2001, before climbing to 29 percent in 2003 and 63 percent in 2009. The increases in acreage share in recent years may be largely due to the commercial introduction in

2003/04 of a new Bt corn variety that is resistant to the corn rootworm, a pest that may be more destructive to corn yield than the European corn borer, which was previously the only pest targeted by Bt corn. Plantings of Bt cotton expanded more rapidly, from 15 percent of U.S. cotton acreage in 1997 to 37 percent in 2001 and 65 percent in 2009.

This paper presents the first part of an ongoing project whose objective is to present a long term relationship between conservation tillage, adoption of GE crops and pesticide use for major crops in the United States. In addition, the project aims to provide some innovative tests on causality using a panel data set. This paper presents preliminary results for soybeans.

Pesticide Use, GE Crops, and Conservation Tillage

Several studies have attempted to establish whether the adoption of conservation tillage and GE crops affects pesticide use. The results depend on the period studied, type of data used, the different approaches to measuring pesticide use, and various statistical procedures. While the results of cross-section studies are informative, these findings are affected by the specific conditions prevailing on the year of the study and may not be representative of the overall situation. On the other hand, many time-series studies have econometric problems

Most previous studies found that adoption of GE crops is associated with lower pesticide use or lower pesticide toxicity. However, while pesticide use rates (in terms of active ingredient) are often lower for adopters of GE crops than for non adopters, some studies suggest that herbicide use on HT soybeans may be slightly higher than herbicide use on conventionally

¹ The term pesticide use in this paper includes herbicides and insecticides.

grown soybeans in the U.S. (Fernandez-Cornejo and Caswell, 2004; Fernandez-Cornejo and McBride, 2002).²

The evidence on the effect of tillage on herbicide use is mixed. Results tend to depend on the type of conservation tillage used, the location, weather, soil type, endemic weed problems, and the metric used to measure pesticide use. In addition, a USDA (1998) report citing Fawcett (1987) observes that herbicide use may decrease with conservation tillage after a few years of adoption: "when a farmer uses conservation tillage, dormant weed seeds in the soil will no longer be transferred to the germination zone near the soil surface by tillage. Consequently, as annual weeds are controlled, the overall weed problem may decrease after a few years when fields are converted to conservation tillage and if effective weed control is practiced."

Conservation Tillage and GE Crops

Researchers have also examined the influence of adoption of GE crops (particularly GE crops with herbicide tolerant traits) on conservation tillage. Measurement of the adoption impact of HT crops on conservation tillage use is complicated because the direction of causality is not certain. Availability of the herbicide-tolerant technology may affect the adoption of conservation tillage, while at the same time the use of conservation tillage may impact the decision to adopt herbicide-tolerant seeds. Therefore, the two decisions must be considered simultaneously. An econometric model developed to address the simultaneous nature of the decisions was developed by Fernandez-Cornejo et al. (2003). The model was used to determine the nature of the relationship between the adoption of HT soybeans and no-till practices using 1997 national survey data. Farmers using no-till for soybeans were found to have a higher probability of adopting HT soybeans, but use of HT soybeans did not significantly affect no-till adoption. This

² Still, glyphosate (the herbicide used in most of the HT crops) is less than one-third as toxic to humans, and not as likely to persist in the environment as the herbicides it replaces (Fernandez-Cornejo and McBride, 2002).

result seemed to suggest that farmers already using no-till found HT seeds to be an effective weed control mechanism that could be easily incorporated into their weed management program. On the other hand, the commercialization of HT soybeans did not seem to encourage the adoption of no-till, at least at the time of the survey in 1997.

Mensah (2007), however, found a two way causal relationship using more recent data. He examined the same issue using a simultaneous adoption model and a 2002 survey of soybean farmers. Mensah found that farmers who adopted no-till were more likely to adopt HT soybeans and, conversely, farmers who adopted the HT technology were more likely to adopt no-till.

In the case of cotton, the evidence points toward a two-way causal relationship. Roberts et al. (2006) evaluated the relationship between adoption of HT cotton seed and conservation tillage practices for Tennessee over time (1992-2004). Using two methods (an application of Bayes' theorem and two-equation logit model), they found that herbicide-tolerant cotton increased the probability that farmer would adopt conservation tillage and, conversely, that farmers that had previously adopted conservation tillage practices were more likely to adopt HT cotton.

Kalaizandonakes and Suntornpithug (2003) also studied the simultaneous adoption of HT and stacked cotton varieties and conservation tillage practices using farm level data. They conclude that conservation tillage practices both "encourage" the adoption of HT and stacked cotton varieties and are encouraged by them. Using state level data from 1997 to 2002 and using a simultaneous equation econometric model, Frisvold et al. (2007) studied the diffusion of herbicide tolerant cotton and conservation tillage. They found strong complementarities between the two technologies. They were able to reject the null hypothesis that the diffusion of one of the technologies is independent of the diffusion of the other one. They also found an increase in the probability of adoption of HT cotton increased the probability of adoption of conservation tillage and vice versa.

In sum, the majority of the empirical evidence point to a two way causal relationship between the adoption of HT crops and conservation tillage. This complementary relationship, in turn, leads us to conclude that the adoption of HT crops indirectly benefits the environment in the form of reduced soil losses and runoff and reduced fuel use.

Data and Research Methodology

Pesticide use in major crops such as soybeans (on a per acre basis) is hypothesized to be related to crop and pesticide prices, the extent of adoption of conservation tillage and the adoption of genetically engineered crops, in addition to factors related to location and weather. We have constructed a panel data set for the 1988-2006 period for the major corn-soybeans producing states. Conservation tillage data are obtained from the Conservation Technology Information Center (CTIC) supplemented by USDA's ARMS data; adoption of GE crops data are obtained from USDA (Fernandez-Cornejo, 2009), crop price data are from USDA's Agricultural Prices and pesticide data are quality adjusted based on chemical usage data from USDA/NASS pesticide use surveys and from the Doane Countrywide Farm Panel Survey. The procedure to quality-adjust the pesticide series is shown in Fernandez-Cornejo et al. (2009) and Vialou et al. (2008) and is summarized below.

Measuring Pesticide Use

In the past, agricultural chemical use has been measured and reported in pounds. This approach is straightforward, but limits the analysis of trends over time and across chemicals. One pound of a pesticide counts the same as one pound of another pesticide that is twice as effective. To account for these differences in characteristics and provide a standard measure of pesticide usage, the prices and quantities of pesticides are adjusted for quality using hedonic estimation as in Fernandez-Cornejo and Jans (1995). This approach allows comparisons of chemical usage

over time, as measures take into account the dynamic efficacy and safety characteristics of the product mix.

More precisely, hedonic methods take into account the concept that inherent differences in pesticide characteristics or quality prevent the direct comparison of observed prices of pesticides over time and across regions. A hedonic price function expresses the price of a good or service as a function of the quantities of the characteristics it embodies. Thus, a pesticide hedonic function may be expressed as w = W(X, D), where w represents the price of pesticide, X is a vector of characteristics or quality variables and D is a vector of other variables. If the main objective of the study is to obtain price indexes adjusted for quality, the only variables that should be included in D are dummy variables, which will capture all price effects other than quality. After allowing for differences in the levels of the characteristics, the part of the price difference not accounted for by the included characteristics will be reflected in the year (or state) dummy coefficients. Inherent differences in pesticide characteristics or quality prevent the direct comparison of observed prices of pesticides over time and across regions. Hence, a hedonic price function expresses the price of a good or service as a function of the quantities of the characteristics it embodies--pesticide potency, hazardous characteristics, and persistence. Quality-adjusted price indices are calculated for pesticides using these hedonic functions. In this study, we use the results of Fernandez-Cornejo et al. (2009) and Vialou et al. (2008) who obtained quality-adjusted price and quantities of pesticide used in corn and soybeans. They adopted a generalized linear form, where the dependent variable and each of the continuous independent variables is represented by the Box-Cox transformation. This is a mathematical expression that assumes a different functional form depending on the transformation parameter, and which can assume both linear and logarithmic forms, as well as intermediate non-linear

functional forms. The analysis employed a new pesticide database that was compiled from USDA pesticide use surveys and the Doane's Countrywide Farm Panel Survey. A detailed, state panel dataset was developed for 1986 to 2007.

Avoiding Spurious Regression Results

In order to minimize the potential for spurious results in regressions using time series, the model variables must be stationary (stationarity is a necessary condition to satisfy an assumption of classical econometrics). Spurious regression results are avoided if all variables are integrated of order zero, I(0). Alternatively, if all variables have unit roots, I(1), spurious regression results may be avoided if the variables are cointegrated.³

Thus, we first examine whether the behavior of the economic variables is consistent with a unit root or not; that is, whether the series is non-stationary or stationary. Typically, this analysis has been carried out using tests such as the augmented Dickey-Fuller test or semiparametric tests, such as the Phillips-Perron test (Ball et al., 2004). The main problem is that, in a finite sample, any unit root process can be approximated by a trend-stationary process. The result is that unit root tests have limited power against the stationary alternative (Ball et al, 2004).

Recently, many researchers have been exploiting the extra information provided by pooling time-series and cross-sectional data and the subsequent power advantages of panel data unit root tests. Starting from the seminal works of Levin and Lin (1993, 2002, 2003) and Im, Pesaran and Shin (1997), many tests have been proposed for unit roots in panel data. Levin and Lin (2002, 2003) show that by combining the time series information with that from the cross-section, the inference about the existence of unit roots can be made more straightforward and

³ Cointegration allows us to consider long run relationships among these variables. Conversely, if a long-run relationship exists between the variables, they must be cointegrated. As a consequence, testing for cointegration among these economic variables implies testing for a long-run relationship among them.

precise, especially when the time series dimension of the data is not very long and similar data may be obtained from a cross-section of units such as countries or industries.

Many tests have been developed to test for unit roots or stationarity in panel datasets (Levin–Lin–Chu, 2002; Harris–Tzavalis, 1999; Breitung, 2000; Breitung and Das, 2005; Im–Pesaran–Shin, 2003; Choi 2001). These tests have as the null hypothesis that the panels contain a unit root. But some of them (Levin–Lin–Chu, 2002; Harris–Tzavalis, 1999) are more useful because their alternative hypothesis is that all the panels are stationary, while for others (e.g., Im–Pesaran–Shin) the alternative hypothesis is that "some panels are stationary."

Because the Levin–Lin–Chu test requires that the ratio of the number of panels to time periods tend to zero asymptotically, it is not well suited to datasets with relatively few time periods. In this paper we use the Harris–Tzavalis test to examine whether the variables contain a unit root (Harris–Tzavalis, 1999; STATA, 2010).

After having examined the stationarity of the variables, we estimate the long term relationship between conservation tillage adoption of biotech crops and pesticide use for soybeans in the United States. We specify two regressions. The first regression considers the adoption of conservation tillage (CTILLSOY), as a function of the adoption of herbicide tolerant soybeans (SOYHT) and the real price of soybean (REL_SOYPRICE). The second regression considers the quantity of quality-adjusted herbicides applied to produce soybeans (QQPESTSOY_HT) as a function of adoption of conservation tillage (CTILLSOY), adoption of herbicide-tolerant soybeans (SOYHT), and the quality adjusted price of herbicides lagged one year (REL_PQPESTSOY_HT_1). In each regression we estimate a fixed effects model and a random effects model.

The fixed effects model is usually used to control for omitted variables. In our case, we use a two-way fixed effects model that captures State and year effects. Using Baltagi's notation (Baltagi, 2001), the fixed effect model is:

$$Y_{it} = \alpha + X'_{it}\beta + u_{it}, \quad i = 1...N; t=1...T$$
 (1)

$$u_{it} = \mu_i + \lambda_t + \nu_{it} \tag{2}$$

where i represent States and t denotes time (year); α is a scalar, β is Kx1 and X_{it} is the observation for State i in time t for the K explanatory variables. μ_i is the unobservable individual specific effect; it is time invariant and accounts for any individual effects not included in the regression (Baltgi, 2001). λ_t is the unobservable time effect; it is individual-invariant and accounts for any time-specific effect not included in the regression; v_{it} is the remainder disturbance In the two-way fixed effects model the μ_i and the λ_t are assumed to be fixed parameters to be estimated. The X_{it} is assumed to be independent of v_{it} for all i and t (Baltgi, 2001).

For the random effects model, the μ_i and λ_t are assumed to be random and independent of the v_{it} and, again, X_{it} is assumed to be independent of μ_i , λ_t and v_{it} for all i and t (Baltagi, 2001).

To estimate the models we use the PANEL procedure from SAS. Fixed effects models, as noted in SAS (2002) "are essentially regression models with dummy variables that correspond to the specified effects. For fixed-effects models, ordinary least squares (OLS) estimation is the

best linear unbiased estimator." For random effects a two stage approach is used. In the first stage we follow SAS and use the estimated error variance components following Fuller and Battese (1975). In the second stage, the PANEL procedure uses the estimated variance components to perform the GLS regression

To test the significance of the dummy variables of the fixed effects model an F test is performed. To choose between the fixed effects and random effects models we use the Hausman test. The period considered is 1988-2006 and 12 major soybean producing states are included in the dataset: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. Table 1 shows the list of the variables and their mean values.

Preliminary Results

The stationarity (unit root) test results using the Harris–Tzavalis (1999) and are shown in table 1. As seen there, all variables are stationary since the null hypothesis that the panel contains unit roots is rejected at the 1 percent level in favor of the alternative hypothesis that the panel is stationary for all the variables.

Table 2 shows the regression results for the fixed effects model of the conservation tillage equation. Table 2A shows the corresponding case with random effects. In both cases the coefficient of the HT soybean adoption variable is positive and highly significant (pvalue=0.0056) indicating that the adoption of herbicide soybeans is impacting positively the adoption of conservation tillage in U.S. soybeans. The elasticity of the adoption of conservation tillage with respect to the adoption of herbicide-tolerant soybeans (at the means) is 0.35, indicating that a one percent increase in adoption of HT soybeans leads to 0.35 percent increase

in adoption of conservation tillage. The Hausman test, comparing fixed and random effects, shows that the null hypothesis of the random effects model being appropriate, i.e., consistent, cannot be rejected.

Table 3 shows the regression results for the fixed effects model of the quality-adjusted quantity of herbicide use equation. Table 3A shows the corresponding case with random effects. In this case the Hausman test allows rejecting the null hypothesis at the 5 percent level, meaning that the random effects model is not consistent. The coefficient of the conservation tillage variable is significant (p value = 0.052) and negative indicating that adoption of conservation tillage is impacting negatively the quality-adjusted quantity of herbicide used (that is, higher adoption of conservation tillage reduces herbicide use). And the elasticity of quality-adjusted pesticide use with respect to adoption of conservation tillage (at the means) is 0.30. On the other hand, the coefficient of the HT soybean adoption variable is not significant, indicating that the direct effect of HT adoption on quality-adjusted herbicide use is not significant.

Concluding Comments

Using a panel data set covering 12 States and 19 years (from 1988 to 2006) we find that a onepercent increase in the adoption of HT soybeans in the U.S. leads to 0.35 percent increase in the
adoption of conservation tillage, confirming the complementary relationship between adoption of
conservation tillage and adoption of HT soybeans found previously using cross-sectional data.

Moreover, an increase of one percent in the adoption of conservation tillage leads to a decrease
in the quantity of herbicide used (adjusted for quality) of 0.30 percent. The effect of adoption of
HT soybeans on the quality-adjusted quantity of herbicides used on soybeans is not significant.

Thus while the adoption of HT soybeans does not lead to a direct decrease in herbicide use, it

does lead to an indirect decrease through its influence in facilitating the use of conservation tillage. The regression results are not spurious because we verified that all the variables examined are stationary based on statistical testing that exploits the extra information provided by the pooling of time-series and cross-sectional data and the subsequent power advantages of panel data unit root tests.

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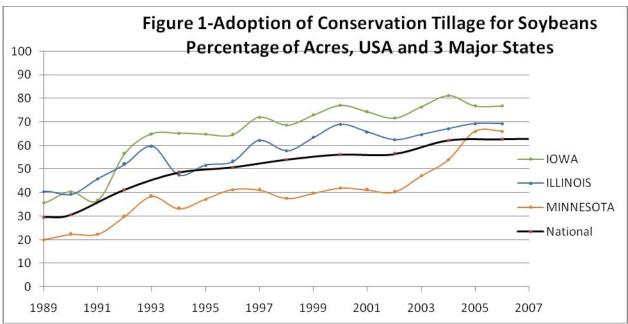
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Source: CTIC (2010).

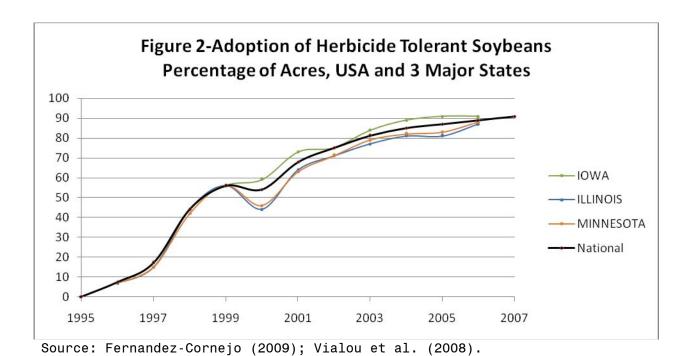


Table 1. Variables: Definitions, Means, and Stationarity Test Results

Variable	Label	Mean	Stationarity? p-value 1/
CTILLSOY	Fraction of soybean acres using conservation tillage	0.475815	5 Yes 0.0004
SOYHT	Fraction of acres in HT soybeans	0.347561	Yes 0.0000
REL_SOYPRICE	Relative soybean price	5.189408	yes 0.0000
QQPESTSOY_HT	Quality-adjusted quantity of herbicides used on soybeans	8.371778	yes 0.0288
REL_PQPESTSOY_HT	Real price of quality-adjusted herbicide use on soybeans	5.718484	Yes 0.0000
REL_PQPESTSOY_HT_1	Lagged REL_PQPESTSOY_HT	5.827536	Yes 0.0000

^{1/} Using the Harris-Tzavalis unit root test for panel data (Harris and Tzavalis (1999). H0 is that panels contain unit roots and Ha is that all panels are stationarity (results obtained using STATA.)

Table 2--Regression Results: Effect of Herbicide Tolerant Soybeans on Conservation Tillage

Fixed Two-Way Estimates

Dependent Variable: CTILLSOY fraction of soybeans acres using conservation tillage

Fit Statistics						
SSE	0.7947	DFE	196			
MSE	0.0041	Root MSE	0.0637			
R-Square	0.8968					
F Test for No Fixed Effects						
Num	DF Den DF	F Value	Pr > F			

196

37.10 <.0001

Parameter Estimates

29

			Standard		
Variable	DF	Estimate	Error	t Value	Pr > t
CS1	1	0.095878	0.0233	4.11	<.0001
CS2	1	0.134906	0.0224	6.01	<.0001
CS3	1	0.160257	0.0211	7.58	<.0001
CS4	1	-0.12513	0.0211	-5.94	<.0001
CS5	1	0.019121	0.0211	0.91	0.3658
CS6	1	-0.08071	0.0207	-3.91	0.0001
CS8	1	0.080784	0.0212	3.82	0.0002
CS9	1	-0.26246	0.0220	-11.95	<.0001
CS10	1	0.075694	0.0222	3.42	0.0008
CS11	1	0.003116	0.0226	0.14	0.8905
TS1	1	-0.23628	0.2099	-1.13	0.2617
TS2	1	-0.19497	0.1170	-1.67	0.0972
TS3	1	-0.183	0.1121	-1.63	0.1043
TS4	1	-0.1508	0.1057	-1.43	0.1554
TS5	1	-0.07413	0.1028	-0.72	0.4716
TS6	1	0.01038	0.1263	0.08	0.9346
TS7	1	0.038051	0.0940	0.40	0.6860
TS8	1	0.042093	0.1251	0.34	0.7368
TS9	1	0.02865	0.1295	0.22	0.8252
TS10	1	0.048348	0.0897	0.54	0.5903
TS11	1	-0.00253	0.0474	-0.05	0.9574
TS12	1	-0.02991	0.0386	-0.78	0.4391
TS13	1	-0.01953	0.0430	-0.45	0.6500
TS14	1	-0.05399	0.0449	-1.20	0.2305
TS15	1	-0.08446	0.0319	-2.64	0.0088
TS16	1	-0.0713	0.0801	-0.89	0.3743
TS17	1	-0.02933	0.0262	-1.12	0.2644
TS18	1	0.006578	0.0295	0.22	0.8240
Intercept	1	0.394537	0.2085	1.89	0.0600
SOYHT	1	0.245397	0.0876	2.80	0.0056
REL_SOYPRICE	1	0.008552	0.0478	0.18	0.8583

Table 2A--Regression Results Conservation tillage and Herbicide Tolerant Soybeans

Random Effects - Fuller and Battese Variance Components (RanTwo)

Dependent Variable: CTILLSOY fraction of soybeans acres using conservation tillage

		S			

SSE	0.9239	DFE	225
MSE	0.0041	Root MSE	0.0641
R-Square	0.1422		

Variance Component Estimates

Variance	Component	for	Cross Sections	0.010379
Variance	Component	for	Time Series	0.006251
Variance	Component	for	Error	0.004054

Hausman Test for Random Effects

DF	m Value	Pr > m
2	0.30	0.8628

Parameter Estimates

			Standard		
Variable	DF	Estimate	Error	t Value	Pr > t
Intercept	1	0.490986	0.1188	4.13	<.0001
SOYHT	1	0.248617	0.0523	4.76	<.0001
REL_SOYPRICE	1	-0.01788	0.0187	-0.95	0.3411

Table 3--Regression Results: Effect of Conservation tillage and Herbicide Tolerant Soybeans on Quality-Adjusted Pesticide Use - Fixed Two Way Estimates

Dependent Variable: QQPESTSOY_HT

Fit Statistics

SSE	1099.0585	DFE	184
MSE	5.9731	Root MSE	2.4440
R-Square	0.8844		

F Test for No Fixed Effects

Num DF	Den DF	F Value	Pr > F
28	184	32.34	<.0001

Parameter Estimates

			Standard		
Variable	DF	Estimate	Error	t Value	Pr > t
CS1	1	18.25545	0.8883	20.55	<.0001
CS2	1	12.19552	0.9111	13.39	<.0001
CS3	1	17.83032	0.9507	18.76	<.0001
CS4	1	1.09636	0.9637	1.14	0.2567
CS5	1	1.426255	0.8554	1.67	0.0972
CS6	1	8.509989	2.7464	3.10	0.0022
CS7	1	6.064476	1.3470	4.50	<.0001
CS8	1	4.867371	0.8785	5.54	<.0001
CS9	1	-1.17569	1.0978	-1.07	0.2856
CS10	1	7.39913	1.0874	6.80	<.0001
CS11	1	2.479295	0.9122	2.72	0.0072
TS1	1	-4.85493	2.5228	-1.92	0.0558
TS2	1	-2.38577	2.5096	-0.95	0.3430
TS3	1	-2.49294	2.4658	-1.01	0.3133
TS4	1	-2.18598	2.4877	-0.88	0.3807
TS5	1	0.793246	2.5001	0.32	0.7514
TS6	1	1.844364	2.4982	0.74	0.4613
TS7	1	2.89115	2.4789	1.17	0.2450
TS8	1	3.424385	2.3086	1.48	0.1397
TS9	1	4.628804	2.1151	2.19	0.0299
TS10	1	3.262461	1.5762	2.07	0.0399
TS11	1	1.463762	1.4668	1.00	0.3196
TS12	1	1.427159	1.4400	0.99	0.3230
TS13	1	0.858095	1.2016	0.71	0.4760
TS14	1	0.740092	1.1320	0.65	0.5141
TS15	1	0.397903	1.1261	0.35	0.7242
TS16	1	0.001767	1.0802	0.00	0.9987
TS17	1	-0.46311	1.0367	-0.45	0.6556
Intercept	1	3.950754	3.2343	1.22	0.2234
CTILLSOY	1	-5.37615	2.7520	-1.95	0.0523
SOYHT	1	1.048856	2.4385	0.43	0.6676
REL_PQPESTSOY_HT_1	1	-0.02549	0.4709	-0.05	0.9569

 ${\bf Table~3A--Regression~Results:~Effect~of~Conservation~tillage~and~Herbicide~Tolerant~Soybeans~on~Quality-Adjusted~Pesticide~Use~-$

Random effects - Fuller and Battese Variance Components (RanTwo)

Dependent Variable: QQPESTSOY_HT

Fit Statistics

SSE	1320.8726	DFE	212
MSE	6.2305	Root MSE	2.4961
R-Square	0.0006		

Variance Component Estimates

Variance	Component	for	Cross Sections	30.78885
Variance	Component	for	Time Series	3.059627
Variance	Component	for	Error	5.973144

Hausman Test for Random Effects

DF	m Value	Pr > m
3	8.17	0.0426