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# Conservation Tillage, Herbicide Use, and Genetically Engineered Crops in the United States: The Case of Soybeans

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This study examines the extent to which adopting herbicide-tolerant (HT) soybeans affects conservation tillage practices and herbicide use. The model is estimated using a state-level panel dataset extending across 12 major soybean-producing states from 1996 to 2006. The results of our analysis suggest that HT adoption induces farmers to adopt conservation tillage practices. Our results also show that HT adoption leads to a decrease in quality-adjusted herbicide use.

***Key words:*** genetically engineered soybeans, herbicide tolerance, herbicide use, technology adoption.

## Introduction

Many of the positive environmental impacts of conservation tillage systems are well documented (National Research Council [NRC], 2010). By leaving substantial amounts of crop residue (at least 30%) on the soil surface (from harvest through planting), conservation tillage reduces soil erosion from wind and water, increases water retention, and reduces soil degradation as well as water and chemical runoff. In addition, conservation tillage reduces the carbon footprint of agriculture (Holland, 2004; NRC, 2010).

Less is known about the interaction of adoption of herbicide-tolerant (HT) crops and conservation tillage, as well as their effects on herbicide use. These are important issues. For example, if adoption of HT crops induces the adoption of conservation tillage, then HT crop adoption indirectly benefits the environment in the form of reduced soil losses and runoff. However, if herbicide use increases with conservation tillage, then (some of) the environmental gains from reduced soil erosion may be offset by increased reliance on herbicides,[1] which are a source of concern for their potential harm to human health and the environment (Fuglie, 1999). In consequence, HT crop adoption, conservation tillage, and herbicide use should be examined together.

This study represents the first part of an ongoing project with the objective of presenting a long-term relationship between adoption of conservation tillage, adoption of HT crops, and herbicide use for major crops in the United States. This article focuses on soybeans.

First, we provide background information on conservation tillage and HT crops. Next, we review the literature on 1) the interaction of the decision to adopt HT seeds and the choice of tillage technology and 2) how herbicide use is impacted by the adoption of HT crops and of conservation tillage. Third, we discuss the data, models, and empirical techniques used in the study. To conclude, we present the results and discuss them.

### *Conservation Tillage*

Conservation tillage systems are cropping production systems that leave at least 30% of crop residues on the soil after planting. There are several types of these systems. For instance, mulch-till systems redistribute at least 30% of crop residues over the entire soil surface. This is a full-width tillage system, usually involving one to three tillage passes over the field, disturbing the soil surface. It is performed prior to and/or during planting (Conservation Technology Information Center [CTIC], 2002). Ridge-till systems leave crop residues undisturbed except for the ridges (up to 1/3 of the crop row width) into which seeds are planted (CTIC, 2011). No-till systems, often considered the most effective, leave 100% of crop residues on the soil surface and the soil is undisturbed from harvest to planting, resulting in the highest percentage of surface being covered by crop residues; this minimizes soil loss and water runoff (Janssen & Hill, 1994).

The use of conservation tillage systems increased steadily throughout the 1980s and 1990s. For instance, while only 30% of soybean farmers used conservation tillage systems in 1996, 63% of soybean farmers used conservation tillage in 2006 (Figure 1). While approximately 33% of corn acres were produced using conservation tillage systems in 1990, 40% of corn acres were produced using conservation tillage systems in 2006.

1. *While the term pesticide includes herbicides, insecticides, and fungicides, in the case of soybeans, most of the pesticides used are herbicides. For example, more than 95% of the pesticides (in pounds of active ingredient) applied to soybeans in 2006 were herbicides. This article focuses on herbicides.*

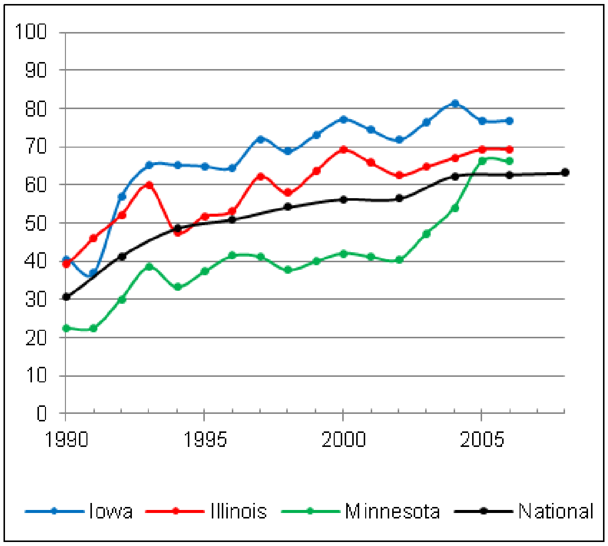


**Figure 1. Adoption of conservation tillage for soybeans (percentage of acres): United States and three major states.**
*Source: CTIC (2010); USDA ARMS data (USDA, 2012).*

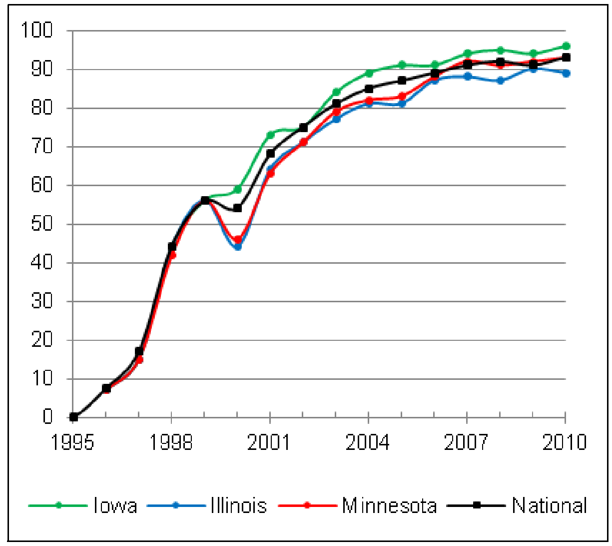


**Figure 2. Adoption of herbicide-tolerant soybeans (percentage of acres): United States and three major states.**
*Sources: Fernandez-Cornejo (2010); Vialou et al. (2008).*

In part, the rapid increase in conservation tillage was facilitated by the availability (since the 1980s) of post-emergent herbicides. Post-emergent herbicides can be applied over crops throughout the growing season (not just before planting, as had previously been the case). Post-emergent herbicides had an especially large impact on the use of no-till production systems because conventional tillage was one of the primary methods of weed control in earlier years.

### HT Crop Adoption

HT crops, developed to survive the 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.

US farmers have adopted genetically engineered (GE) crops widely since their introduction in 1996. Soybeans genetically engineered with herbicide-tolerant traits have been the most widely and rapidly adopted GE crop in the United States, followed by HT cotton (Fernandez-Cornejo, 2010). Based on US Department of Agriculture (USDA) survey data, adoption of HT soybeans went from 17% of US soybean acreage in 1997 to 68% in 2001 and 93% in 2010 (Figure 2). Plantings of HT cotton expanded from about 10% of US acreage in 1997 to 56% in 2001 and 78% in 2010. The adoption of HT corn, which had been slower in previous years, has also accelerated, reaching 70% of US corn acreage in 2010.

### HT Crops and Conservation Tillage

Anecdotal evidence indicates that the adoption of HT crops (particularly HT soybeans) has facilitated the use of conservation tillage systems because the use of HT seeds tends to make weed control more effective and less costly (Carpenter & Gianessi, 1999).

Researchers have carried out empirical analyses to examine the interaction of the decisions to adopt HT crops and conservation tillage systems. While most studies have found that the decisions to adopt conservation tillage and to adopt HT seeds are correlated (Fernandez-Cornejo & Caswell, 2006), it is difficult to demonstrate whether HT adoption induces farmers to adopt conservation tillage practices, or whether adoption of conservation tillage practices induces farmers to adopt HT seeds.[2]

Fernandez-Cornejo et al. (2003) presented an econometric model to address the potentially simultaneous nature of the decisions. This model was estimated using national survey data collected in 1997 (the second year of adoption) and tested using the Wu-Hausman statistic. They found that soybean farmers using no-till practices had a higher probability of adopting HT soybeans. However, HT soybean adoption did not appear to significantly affect no-till adoption rates. These results seemed to suggest that farmers already using no-till practices 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 adoption of HT soybeans did not seem to encourage the adoption of no-till practices, but this may be due to the relatively low adoption rate of HT soybeans in 1997 (17% adoption).

Mensah (2007) identified a two-way relationship between adoption of HT seeds and conservation tillage using a simultaneous adoption model and a 2002 survey of soybean farmers. Using Wu-Hausman tests, Mensah found that farmers who adopted no-till practices were more likely to adopt HT soybeans and that adopters of HT soybeans were more likely to adopt no-till systems.

Roberts, English, Gao, and Larson (2006) analyzed data of cotton farmers in Tennessee from 1998 to 2004 using two methods. First, they compared the conditional probabilities (using Bayesian methods) of adopting HT cotton given that conservation tillage was adopted and conversely. Second, they estimated simultaneously (using 3-stage least squares estimation) two binomial logit models. They found that adoption of HT cotton increased the probability that farmers would adopt conservation tillage. They also found that farmers who had previously adopted conservation tillage were more likely to adopt HT cotton. However, Roberts et al. (2006) found that the influence of adoption of conservation tillage on adoption of HT cotton weakened over time. And in the later years of their sample period (2003-2004), differences in tillage had minimal influence on the probability of adopting HT seeds because almost all the acreage in the sample used HT seed, regardless of the tillage method.

Kalaitzandonakes and Suntornpithug (2003) used a simultaneous equation system for the adoption of Bt cotton, HT cotton, stacked (Bt/HT) cotton, and conservation tillage using farm data of several cotton-producing states in 1998-1999. The four-equation model was estimated using the generalized method of moments (GMM). They found that adoption of conservation tillage both encourages the adoption of HT cotton and is encouraged by it.

Using state-level data for 1997-2002, Frisvold, Boor, and Reeves (2009) found that the diffusion of conservation tillage speeds diffusion of HT cotton and vice versa, suggesting that the two technologies are complementary. Frisvold et al. (2009) estimated that a 1% increase in a state's adoption rate for HT cotton increases the state's adoption rate for conservation tillage by 0.48%. The influence of adoption of conservation tillage on adoption of HT cotton was weaker: a 1% increase in the adoption rate of conservation tillage increases the adoption rate of HT cotton by 0.16%.

In sum, there are many differences among previous studies—the crops studied, periods considered, unit of analysis (farm vs. state level), methodology, and even in the concepts involved. For that reason, caution should be exercised to make definitive conclusions. Still, in most cases we examined, adoption of HT crops has facilitated the use of conservation tillage systems and vice versa. This implies that by encouraging farmers to adopt conservation tillage, HT crop adoption indirectly benefits the environment by reducing soil losses and erosion, runoff, fuel use, and the carbon footprint of agriculture (NRC, 2010, and references cited therein).

### Herbicide Use

Several studies have examined the adoption of conservation tillage, HT crops, and herbicide use. The results depend on the period studied, the data analyzed, and the methodology employed. For instance, most researchers analyze cross-sectional data and measure herbicide use by aggregating the total pounds of active ingredients applied. While the results of cross-sectional studies are informative, the findings of these studies can be biased by unobservable conditions prevailing in the year of the study. Moreover, when herbicide use is aggregated across active ingredients, it is often implicitly assumed that all active ingredients have the same characteristics (i.e., potency, toxicity, etc.).

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2. *Causality is a complex concept that has evolved over many centuries. Aristotle, Hume, and Stuart Mill—and, more recently Simon, Zellner, and Granger—addressed the subject (see review by Hoover, 2008). As Hoover (2008) notes, in the 20th Century it was understood that, unlike correlation, regression has a natural direction (the regression of Y on X does not produce coefficient estimates that are the algebraic inverse of those from the regression of X on Y; "The direction of regression should respect the direction of causation." However, as Hoover also observes, "Although regressions may have a natural causal direction, there is nothing in the data on their own that that reveal which direction is the correct one." This is also related to the problem of econometric identification, as exogenous variables can be considered as "causes" of endogenous variables. Causality also has been defined explicitly using a modern probabilistic approach by Granger (1969). This is a data-based approach developed to apply to time series models (Hoover, 2008).*

**Table 1. Summary statistics of main variables, US soybean farmers, 1996-2006.**

| Variable | Label | Means |
|---|---|---|
| **Conservation tillage adoption** | Share of acreage under conservation tillage | 0.55 |
| **HT soybean adoption** | Share of acreage planted with HT soybean seeds | 0.60 |
| **Relative soybean price** | Soybean price (relative to corn) | 4.61 |
| **Quality-adjusted herbicide use** | Quality-adjusted quantity of herbicide used, index | 9.37 |
| **Quality-adjusted herbicide price** | Quality-adjusted herbicide price, index | 5.12 |

*Note: Summary statistics are calculated from state-level means.*
*Sources: See data section*

### *Herbicide Use and HT Crops*

While most studies show that insecticide use rates (in terms of active ingredient) are lower for adopters of Bt crops than for nonadopters, in the case of HT crops the evidence is less clear. Particularly in the case of soybeans, some studies suggest that herbicide use on HT soybeans may be slightly higher than herbicide use on conventionally grown soybeans in the United States (Fernandez-Cornejo & Caswell, 2006; Fernandez-Cornejo & McBride, 2002; NRC, 2010). However, glyphosate (the herbicide used on most HT crops) is less toxic to humans and not as likely to persist in the environment as the herbicides it replaces (Fernandez-Cornejo & McBride, 2002; NRC, 2010). Consequently, increased herbicide use on HT soybeans is not necessarily indicative of worse environmental outcomes.

### *Herbicide Use and Conservation Tillage*

There is no clear consensus on how conservation tillage affects herbicide use. Results tend to depend on the type of conservation tillage system employed, the location, the weather, the soil type, the metric used to measure herbicide use, and endemic pest pressure. For example, a USDA report (1998, p. 28) 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." Knake (1989, p. 71) states that, "as tillage is reduced, some weeds (such as velvetleaf) may become less of a problem. Other weeds such as fall panicum, mare's tail, hemp dogbane, and common milkweed may increase." Using 1991-1992 Cornbelt data, Fuglie (1999, p. 133), finds "no evidence that herbicide or fertilizer application rates are higher on fields with conservation tillage systems compared with fields with conventional tillage." On the other hand, analyses of Cropping Practices Survey data collected for corn and soybeans from 1990 to 1995 (USDA, 1998) showed that herbicide application rates were higher for conservation tillage than for conventional tillage systems. Holland (2004) shows that conservation tillage not only influences the quantity of herbicides used but also that tillage has an effect on the leaching losses of herbicides. He also observes that, by improving soil structure, conservation tillage may also reduce the risks of runoff and pollution of surface water with pesticides.

## Data and Research Methodology

Herbicide use in soybeans is hypothesized to be related to location, weather (temperature and precipitation during the plant growing season), crop prices, herbicide prices, tillage practices, and HT adoption decisions. We have constructed a panel dataset of the major soybean-producing states[3] for 1996 through 2006 using tillage data obtained from the Conservation Technology Information Center (CTIC, 2010) for the years 1996-2004, supplemented by USDA's ARMS data for more recent years;[4] HT adoption rates obtained from the USDA (Fernandez-Cornejo, 2010); crop prices obtained from USDA's *Agricultural Prices Summary*; and data on herbicide use obtained from USDA's *Agricultural Chemical Usage* reports (USDA National Agricultural Statistics Services [NASS], 2006, and other years), supplemented by data from the Doane Countrywide Farm Panel Survey. Table 1 provides descriptive statistics for the main variables in the dataset.

3. *Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.*
4. *Unlike earlier years, CTIC data for 2005 and 2006 covers only a few counties. For example, only 305 counties were included in the 2006 data (CTIC, 2011).*

Because herbicides contain active ingredients with different characteristics, aggregating herbicide-use statistics across herbicide types produces results that are difficult to interpret. In order to analyze herbicide trends across states and over time while accounting for changes in the quality of the herbicides used, we use quality-adjusted indices of herbicide prices and quantities. The procedure used to create these indices is discussed at length in Fernandez-Cornejo and Jans (1995); Fernandez-Cornejo, Nehring, Newcomb, Grube, and Vialou (2009); and Vialou, Nehring, Fernandez-Cornejo, and Grube (2008). This approach is briefly discussed below.

### Measuring Herbicide Use

Agricultural pesticide use is typically measured and reported in pounds of active ingredient. This approach is straightforward, but has limitations. For instance, one pound of a fairly potent herbicide is not directly comparable to one pound of another herbicide that is twice as effective, In order to compare herbicide use across states and over time, it is necessary to account for differences in herbicide quality.

The first step in accounting for these differences entails defining "quality." In this study we follow Fernandez-Cornejo and Jans (1995) and consider three measures of herbicide quality—potency, hazardous characteristics, and persistence.[5] Herbicide potency, a proxy for "effectiveness," is calculated by taking the inverse of the application rate per crop year. The application rate per crop year (which can be viewed as the dosage) is equal to the number of pounds of active ingredient applied per acre in one application multiplied by the number of applications made in a year. Hazardous characteristics are measured by the chronic scores described in Kellogg, Nehring, Grube, Goss, and Plotkin (2002). Persistence is measured by the herbicide half life. Table 2 presents quality measures for the most commonly used herbicide active ingredients applied to soybeans in 1996 and 2006.

The second step in quality-adjusting herbicide use involves creating an index of quality-adjusted prices and quantities. Following Fernandez-Cornejo and Jans (1995), we estimate a hedonic price function that explicitly models herbicide prices as a function of the characteristics that the herbicides embody. Prices are specified using the following hedonic function: $w = W(\boldsymbol{X}, \boldsymbol{D})$, where $w$ represents the price of herbicide, $\boldsymbol{X}$ is a vector of herbicide quality characteristics variables and $\boldsymbol{D}$ is a vector of year dummy variables. The variables in $\boldsymbol{X}$ (in this case, we include potency, toxicity, and soil half-life) control for differences in herbicide "quality." The variables in vector $\boldsymbol{D}$ capture all price effects other than quality. The parameter estimates for the dummy variables in $\boldsymbol{D}$ are used to create the quality-adjusted price indices.

The third step in quality-adjusting herbicide use is to divide herbicide expenditures by the index of quality-adjusted prices. The result of this calculation is a quality-adjusted quantity.

In this study, we use the results of Fernandez-Cornejo et al. (2009) and Vialou et al. (2008), who obtained quality-adjusted herbicide prices and quantities for soybeans.[6]

**Table 2. Quality characteristics for selected commonly-used soybean herbicides in 1996 and 2006.**

| | Rate per crop year (Lbs Ai / crop acres)[1] | Chronic toxicity score[2] | Soil half life (days)[3] | % of use |
|---|---|---|---|---|
| **Herbicides, 1996** | | | | |
| Pendimethalin | 1.18 | 70 | 90 | 23 |
| Trifluralin | 0.85 | 5 | 60 | 17 |
| Glyphosate | 0.7 | 700 | 47 | 15 |
| Alachlor | 2.49 | 2 | 15 | 8 |
| Bentazone | 0.71 | 200 | 20 | 7 |
| Metolachlor | 2.19 | 70 | 90 | 7 |
| 2,4-D | 0.54 | 70 | 10 | 6 |
| Others | | | | 17 |
| **Herbicides, 2006** | | | | |
| Glyphosate | 1.1 | 700 | 47 | 85 |
| 2,4-D | 0.54 | 70 | 10 | 4 |
| Pendimethalin | 0.89 | 70 | 90 | 3 |
| Metolachlor | 1.07 | 70 | 90 | 1 |
| Trifluralin | 0.87 | 5 | 60 | 2 |
| Others | | | | 5 |

*[1] Higher rate indicates lower potency of the herbicide; more potent herbicides require a lower rate to achieve a degree of pest control.*
*[2] A higher score indicates lower chronic toxicity.*
*[3] A higher half life indicates that the herbicide is more persistent in the environment.*
*Sources: See data section; Kellogg et al. (2002)*

5. *A "high quality" herbicide would be potent, non-hazardous, and dissipate quickly.*

### *Model Selection and Testing*

The purpose of our study is to determine a long-term relationship between the use of conservation tillage in soybean fields, adoption of herbicide-tolerant soybeans, and herbicide use in the United States. However, in order to determine the appropriate specification for our model, it is necessary to test certain assumptions about the data.

First, we tested whether the model variables are stationary (i.e., whether the random process generating the variables changed over time). The model variables must be stationary in order to minimize the potential for spurious results in regressions using time-series or panel data. To test for stationarity we used a panel unit root test developed by Levin, Lin, and Chu (2002). As shown in Appendix 1 (Table A1), we determined that the model variables are stationary.

After determining that the model variables were stationary, we used Granger Causality Tests that had been developed by Granger (1969); we determined that adoption of HT soybean "Granger-causes" conservation tillage adoption for soybeans (Appendix 2). This means that state-level HT soybean adoption rates contain information that is useful in predicting state-level conservation tillage rates. However, conservation tillage adoption does not Granger-cause the adoption of HT soybean (Table A2).[7] Consequently, we model conservation tillage rates as a function of HT soybean adoption.

Next, we used Hausman tests developed by Wooldridge (2002) to test whether state-level HT soybean adoption rates were exogenous to 1) state-level conservation tillage rates and 2) quality-adjusted herbicide use. As shown in Appendix 3, the results of the Hausman tests allow us to conclude that state-level HT soybean adoption rates are exogenous to state-level tillage rates and state-level quality-adjusted herbicide use for the 1996 to 2006 period (Appendix 3). Because the Granger Causality tests indicate that state-level HT soybeans adoption rates can be used to predict state-level conservation tillage rates, and because the Hausman tests indicate that HT adoption rates are exogenous, our data can be analyzed using a recursive, two-equation system. Ultimately, we specified two regressions.

$$ConsTill_{it} = \alpha + \beta_{HT}\, HT_{it} + \beta_{Psoy}\, Psoy_{it\text{-}1} + u_{1it} \qquad (1)$$

$$QAHerb_{it} = \alpha + \beta_{C}\, ConsTtill_{it} + \beta_{HT}\, HT_{it} + \beta_{Psoy}\, Psoy_{it\text{-}1} + \beta_{PQAH}\, PQAHerb_{it\text{-}1} + u_{2it}\,, \qquad (2)$$

where $ConsTill_{it}$ represents the adoption rate of conservation tillage (percentage acres planted using conservation tillage) in state $i$, at time $t$; $HT_{it}$ represents the adoption rate of HT soybeans (percentage of acres that farmers plant with HT seeds); $Psoy_{it\text{-}1}$ represents lagged soybean prices (relative to corn); $QAHerb_{it}$ represents quality-adjusted quantity of herbicide used; and $PQAHerb_{it\text{-}1}$ represents lagged quality-adjusted herbicide price.

The first regression models conservation tillage rates as a function of the adoption rate of HT soybeans and the real price of soybeans. The second regression models quality-adjusted quantity of herbicide applied to soybeans as a function of the adoption rate of conservation tillage, the HT soybean adoption rates, and lagged quality-adjusted herbicide price.

Given the panel structure of the data, either fixed effects or random effects are potential estimators of the parameters in Equations 1 and 2. After all, both fixed- and random-effects models control for unobserved or omitted time-invariant, observation-specific variation. Using Hausman tests, we conclude that both the random-effects and the fixed-effects estimators are consistent in both equations (see Appendix 4). However, the random-effects model is more efficient than the fixed-effects model (Wooldridge, 2002). Consequently, we use random effects.

## Main Results

Table 3 shows the regression results for the random-effects model of Equation 1, which analyzes the effect of HT adoption on conservation tillage adoption. Our results indicate that HT soybean adoption has a positive and highly significant (p value < 0.0001) impact on

*6. Fernandez-Cornejo et al. (2009) and Vialou et al. (2008) estimated the hedonic price equations using a generalized linear form, where w and X were rescaled using the Box-Cox transformation. The data analyzed in these studies were compiled from USDA pesticide use surveys and the Doane Countrywide Farm survey.*

*7. That is, state-level conservation tillage adoption rates do not contain information that is useful in predicting HT adoption rates. This result is not comparable to results of previous work discussed in our literature review because the concept of causality implicit in those studies is not equivalent to that used in this work. Additionally, most previous work included beginning and mid-years of adoption of HT soybeans while this study includes 11 years of adoption. As Robert et al. (2006) argued, differences in tillage have minimal influence in the adoption of HT seeds when a large portion of the acreage uses HT seed, regardless of the tillage method.*

**Table 3. Effect of HT soybean adoption on conservation tillage—Random effects model, 1996-2006, for US soybean farmers.**

| | | |
|---|---|---|
| **Observations** | 132 | |
| **R-squared** | 0.17 | |
| **Variable** | **Parameter estimate** | **P-value** |
| HT soybean adoption | 0.19 *** | <0.0001 |
| Lagged relative soybean price | 0.02 ** | 0.03 |
| Constant | 0.34 *** | <0.0001 |

**** indicates that p<0.01, ** indicates that p<0.05, * indicates that p<0.1*

*Source: Model results*

**Table 4. Elasticities of conservation tillage and quality-adjusted herbicide use with respect to HT soybean adoption.**

| Dependent variable | Elasticity |
|---|---|
| **Conservation tillage** | 0.21 |
| **Quality-adjusted herbicide use** | -0.30 |

*Source: Model results*

adoption of conservation tillage amongst US soybean farmers. This suggests that farmers who adopt HT soybean seeds are also more likely to adopt conservation tillage systems than farmers using conventional seeds. Thus, in addition to shifting usage from relatively toxic traditional herbicides (such as Trifluralin and Pendimethalin) to glyphosate (which is known to be relatively benign), HT adoption induces farmers to adopt more environmentally friendly tillage techniques.

Expressing the results of Table 3 as elasticities, we find that the elasticity of the adoption of conservation tillage with respect to the adoption of herbicide-tolerant soybeans (at the means) is 0.21 (Table 4). This means that a 1% increase in adoption of HT soybeans leads to a 0.21% increase in adoption of conservation tillage.[8]

Table 5 shows the regression results for the random-effects model of Equation 2, which analyzes how HT adoption affects quality-adjusted herbicide use. Our results indicate that HT adoption has a very significant impact on quality-adjusted herbicide use but that conservation tillage does not significantly affect quality-adjusted herbicide use. Given that the use of HT seeds induces farmers to shift herbicide usage towards glyphosate, it is not surprising that adopting HT seeds induces farmers to use fewer quality-adjusted pounds.

**Table 5. Effect of HT soybean adoption and conservation tillage on quality-adjusted herbicide use random effects model, 1996-2006, for US soybean farmers.**

| | | |
|---|---|---|
| **Observations** | 132 | |
| **R-squared** | 0.33 | |
| **Variable** | **Parameter estimate** | **P-value** |
| Conservation tillage | 0.72 | 0.78 |
| HT soybean adoption | -4.67 *** | <0.001 |
| Lagged relative soybean price | 0.04 | 0.81 |
| Lagged quality-adjusted herbicide price | 0.22 | 0.55 |
| Constant | 10.36 ** | 0.02 |

**** indicates that p<0.01, ** indicates that p<0.05, * indicates that p<0.1*

*Source: Model results*

After all, glyphosate is less toxic than many other herbicides.

From the results of Table 5 we calculated that the elasticity of quality-adjusted quantity of herbicide use with respect to HT adoption (at the means) is -0.30 (Table 4). This means that a 1% increase in adoption of HT soybeans leads to a 0.3% decrease in the quality-adjusted quantity of herbicide use.

## Conclusions

Using a panel-data set covering 12 states and 11 years (from 1996 to 2006), we find that HT soybean adoption leads to a significant increase in the adoption of conservation tillage. A 1% increase in HT soybean adoption leads to a 0.21% increase in conservation tillage. In addition, HT soybean adoption leads to a decrease in the quality-adjusted quantity of herbicide used: a 1% increase in HT soybean adoption leads to 0.3% decrease in quality adjusted herbicide use. Thus, this study finds that the adoption of herbicide-tolerant crops benefits the environment directly by reducing quality-adjusted herbicide use and indirectly by increasing conservation tillage.

In coming to these conclusions, we verified that 1) the data-generating process was stationary over the course of the study period; 2) state-level HT soybean adoption rates are exogenous to state-level conservation tillage rates and state-level estimates of quality-adjusted herbicide use; and 3) while state-level HT soybean adoption rates contain information that can be used to predict state-level tillage rates (HT soybean adoption rates "Granger cause" conservation tillage rates), state-level tillage rates do not contain information that can be used to predict state-level HT soybean adoption rates

8. *This is about half of the effect found by Frisvold et al. (2009) for the case of HT cotton.*

(conservation tillage rates do not "Granger cause" HT soybean adoption rates).

## References

Ball, E., Hallahan, C., & Nehring, R. (2004). Convergence of productivity: An analysis of the catch-up hypothesis within a panel of states. *American Journal of American Agriculture*, *86*(4), 1315-1321.

Baltagi, B.H. (2001). *Econometric analysis of panel data* (2nd Ed.). Hoboken, NJ: Wiley.

Carpenter, J., & Gianessi, L. (1999). Herbicide tolerant soybeans: Why growers are adopting Roundup Ready varieties. *AgBioForum*, *2*(2), 65-72. Available on the World Wide Web: http://www.agbioforum.org.

Conservation Technology Information Center (CTIC). (2002, November). *Tillage type definitions*. West Lafayette, IN: Author. Available on the World Wide Web: http://www.ctic.purdue.edu/resourcedisplay/322/.

CTIC. (2010). *National crop residue management survey* [database]. West Lafayette, IN: Author. Available on the World Wide Web: http://www.ctic.purdue.edu/crm.

CTIC. (2011). *National crop resisue management survey* [database]. West Lafayette, IN: Author. Available on the World Wide Web: http://www.ctic.purdue.edu/crm.

Fawcett, R. (1987). Overview of pest management systems. In T. Logan, J. Davidson, J. Baker, & M. Overchash (Eds.), *Effects of conservation tillage on groundwater quality: Nitrates and pesticides* (pp. 90-112). Chelsea, MI: Lewis Publishers.

Fernandez-Cornejo, J. (2010). *Adoption of genetically engineered crops in the U.S.* (database). Washington, DC: US Department of Agriculture, Economic Research Service (ERS). Available on the World Wide Web: http://www.ers.usda.gov/Data/BiotechCrops/.

Fernandez-Cornejo, J., & Caswell, M. (2006, April). *The first decade of genetically engineered crops in the United States* (Economic Information Bulletin EIB-11). Washington, DC: USDA ERS.

Fernandez-Cornejo, J., & Jans, S. (1995). Quality-adjusted price and quantity indices for pesticides. *American Journal of Agricultural Economics*, *77*(August), 645-659.

Fernandez-Cornejo, J., Klotz-Ingram, C., Heimlich, R., Soule, M., McBride, W., & Jans, S. (2003). Economic and environmental impacts of herbicide-tolerant and Bt crops in the United States. In N. Kalaitzandonakes (Ed.), *The economic and environmental impacts agbiotech: A global perspective* (pp. 63-88). New York: Kleuwer Academic.

Fernandez-Cornejo, J., & McBride, W.D. (2002). *Adoption of bioengineered crops* (Agricultural Economic Report AER-810). Washington, DC: USDA ERS.

Fernandez-Cornejo J., Nehring, R., Newcomb, E., Grube, A., & Vialou, A. (2009, July 27). *Recent trends in pesticide use in U.S. agriculture*. Paper presented at the Agricultural and Applied Economics Association (AAEA) Annual Meeting, Milwaukee, WI.

Frisvold, G., Boor, A., & Reeves, J. (2009). Simultaneous diffusion of herbicide resistant cotton and conservation tillage. *AgBioForum*, *12*(3&4), 249-257. Available on the World Wide Web: http://www.agbioforum.org.

Fuglie, K.O. (1999). Conservation tillage and pesticide use in the cornbelt. *Journal of Agricultural and Applied Economics*, *31*(1), 133-147.

Fuller, W.A., & Battese, G.E. (1974). Estimation of linear models with crossed-error structure. *Journal of Econometrics*, *2*, 67-78.

Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424-438.

Hausman, J.A. (1978). Specification tests in econometrics. *Econometrica*, *46*(6), 1251-1271.

Hausman, J.A. (1983). Specification and estimation of simultaneous equation models. In Z. Griliches & M. Intriligator (Eds.), *Handbook of econometrics* (Volume 1, Chapter 7). Amsterdam: North Holland.

Holland, J.M. (2004). The environmental consequences of adopting conservation tillage in Europe: Reviewing the evidence. *Agriculture, Ecosystems and Environment*, *103*(2004), 1-25.

Hoover, K.D. (2008). Causality in economics and econometrics. In S.N. Durlauf & L.E. Blume (Eds.), *The new Palgrave dictionary of economics* (2nd Ed.). New York: Palgrave Macmillan. Available on the World Wide Web: http://www.dictionaryofeconomics.com/article?id=pde2008_C000569.

Im, K.S., Pesaran, M.H., & Shin, Y. (1997). *Testing for unit roots in heterogeneous panels*. Cambridge: University of Cambridge, Department of Applied Economics.

Janssen, C., & Hill, P. (1994, November). *What is conservation tillage?* (Conservation Tillage Series CT-1). West Lafayette, IN: Purdue University, Cooperative Extension Service.

Kalaitzandonakes, N., & Suntornpithug, P. (2003). Adoption of cotton biotechnology in the United States: Implications for impact assessment. In N. Kalaitzandonakes (Ed.), *The economic and environmental impacts agbiotech: A global perspective* (pp. 103-118). New York: Kleuwer Academic.

Kellogg, R., Nehring, R., Grube, A., Goss, D.W., & Plotkin, S. (2002). Environmental indicators of pesticide leaching and runoff from farm fields. In V.E. Ball & G. Norton (Eds.), *Agricultural productivity: Measurement and sources of growth* (pp. 11-36). Boston: Kluwer Academic Publishers.

Knake, E.L. (1989). Weed control for resource conservation. In *Tillage system and the agricultural environment: Proceedings from Illinois Tillage Conferences* (pp. 71-82). Urbana, IL: University of Illinois at Urbana-Champaign, Cooperative Extension Service.

Levin, A., & Lin, C.F. (1992). *Unit root tests in panel data: Asymptotic and finite sample properties* (Discussion Paper

Series 92-23). San Diego, CA: University of San Diego, Department of Economics.

Levin, A., & Lin, C.F. (1993). *Unit root tests in panel data: New results* (Discussion Paper Series 93-56). San Diego, CA: University of San Diego, Department of Economics.

Levin, A., Lin, C.F., & Chu, C. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics*, *108*, 1-24.

Mensah, E.C. (2007). *Economics of technology adoption: A simple approach*. Saarbrücken, Germany: VDM Verlag Dr. Müller.

National Research Council (NRC). (2010, April). *The impact of genetically engineered crops on farm sustainability in the United States*. Washington, DC: The National Academies Press.

Roberts, R.K., English, B.C., Gao, Q., & Larson, J.A. (2006). Simultaneous adoption of herbicide-resistance and conservation-tillage cotton technologies. *Journal of Agricultural and Applied Economics*, *38*(3), 629-643.

SAS. (2010). *Overview: PANEL procedure, SAS/ETS 9.2 user's guide*. Cary, NC: SAS Institute, Inc.

US Department of Agriculture (USDA), Economic Research Service (ERS) in collaboration with the Natural Resources Conservation Service. (1998). *The economic and environmental and costs of conservation tillage*. Washington, DC. February.

USDA, ERS. (2012). *ARMS farm financial and crop production practices* [online database]. Washington, DC: Author.

USDA, National Agricultural Statistics Services (NASS). (2006, May). *Agricultural chemical usage: 2005 field crops summary.* Washington, DC: Author. Available on the World Wide Web: http://usda01.library.cornell.edu/usda/nass/AgriChemUsFC//2000s/2006/AgriChemUsFC-05-17-2006.pdf.

Vialou, A., Nehring, R., Fernandez-Cornejo, J., & Grube, A. (2008, July 27). *Impact of GMO crop adoption on quality-adjusted pesticide use in corn and soybean states: A full picture*. Paper presented at the AAEA Annual Meeting, Orlando, FL.

Wooldridge, J.M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, MA: MIT Press.

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## Appendix 1. Testing the Stationarity of the Data Generating Processes

In order to meet a necessary condition of classical econometrics and minimize the potential for spurious results in regressions using time-series or panel data, the model variables must be stationary; in other words, the random process generating the variables should not change over time. Typically, stationarity tests have been carried out using the augmented Dickey-Fuller test—or semiparametric tests—such as the Phillips-Perron test (Ball, Hallahan, & Nehring, 2004). The main problem with these tests is that, in a finite sample, any unit root process can be approximated by a trend-stationary process. This implies that unit root tests have limited power against the stationary alternative (Ball et al., 2004). Recently, researchers have exploited the extra information provided by pooling time-series and cross-sectional data. Unit root tests for panel data have been created to exploit the advantages of these datasets. Building on the work of Levin and Lin (1992, 1993); Levin et al. (2002); and Im, Pesaran, and Shin (1997), many unit root tests for panel data have been proposed. Levin et al. (2002) showed that combining time-series and cross-sectional information makes it easier to infer the existence of unit roots, 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.

**Table A1. Levin-Lin-Chu panel unit root test statistics (with time trend).**

| Variable | Adjusted test statistic | P-value | Stationarity |
|---|---|---|---|
| **Conservation tillage adoption** | -4.53 | <0.0001 | Yes |
| **HT soybean adoption** | -5.08 | <0.0001 | Yes |
| **Relative soybean price** | -7.91 | <0.0001 | Yes |
| **Quality-adjusted herbicide use** | -3.77 | <0.0001 | Yes |
| **Quality-adjusted herbicide price** | -3.01 | <0.0001 | Yes |

*Source: Model results*

In this article, we use a panel unit root test developed by Levin et al. (2002). This test is particularly useful because the alternative hypothesis is that all the panels are stationary. As shown in Table A1, the test results indicate that the variables are stationary.

## Appendix 2. Assessing Granger Causality: State-level Conservation Tillage and HT Soybean Adoption

We tested the direction of causality amongst our primary variables of interest using the Granger causality test. In general, this statistical procedure tests whether one time series is useful in forecasting another. Thus, a time

**Table A2. Assessing the simultaneity of state-level conservation tillage and HT soybean adoption—Granger causality test results.**

| Independent variables | Conservation tillage | P-value | HT soybean adoption | P-value |
|---|---|---|---|---|
| **Lagged conservation tillage adoption** | 0.41 ** | 0.015 | 0.07 | 0.172 |
| **Lagged HT soybean adoption** | 0.18 ** | 0.014 | 0.30 *** | 0.005 |
| **Constant** | 0.28 *** | 0.003 | 0.56 *** | <.0001 |

**** indicates that p<0.01, ** indicates that p<0.05, * indicates that p<0.1*
*Note: State and year fixed effects not shown.*
*Source: Model results*

**Table A3. Assessing the exogeneity of HT soybean adoption, Hausman test results (second stage).**

| $H_0$ = HT soybean adoption is exogenous; no correlation between the first stage residuals and the dependent variables. | | | | |
|---|---|---|---|---|
| **Independent variables** | **Conservation tillage** | **P-value** | **Quality-adjusted herbicide use** | **P-value** |
| **HT soybean residual [1]** | -0.39 | 0.13 | 14.39 | 0.22 |

*Source: Model results*
**** indicates that p<0.01, ** indicates that p<0.05, * indicates that p<0.1*
*[1] The HT soybean residuals were calculated using the results of a separate regression (first stage). The first stage of the endogeneity test entails regressing state-level adoption rates for HT soybeans by the lagged relative soybean price, the lagged quality-adjusted herbicide price, select weather variables, and an indicator for whether weeds in a state had developed herbicide resistance.*
*Note: For the sake of simplicity, this table excludes parameter estimates for the state and year fixed effects, as well as the other explanatory variables: 'HT soybean adoption rates' and 'lagged relative soybean prices.'*

series $X$ is said to Granger-cause $Y$ if it can be shown—usually through a series of t-tests and F-tests on lagged values of $X$ (and with lagged values of $Y$ also included)—that those $X$ values provide statistically significant information about future values of $Y$.

The results shown in Table A2 indicate that state-level HT soybean adoption rates Granger-cause conservation tillage adoption rates at the 5% level (p-value = 0.014), but conservation tillage rates do not Granger-cause HT soybean adoption rates (p-value = 0.17).

## Appendix 3. Assessing the Exogeneity of State-level HT Soybean Adoption

Many analyses of cross-sectional, farmer-level data treat HT adoption as endogenous. This is reasonable because it is likely that unobserved, farmer-specific factors affect both HT adoption decisions and outcomes like profits or yields. However, it was not clear that state-level HT adoption rates are endogenous in a panel setting. Because endogeniety has the potential to bias statistical results, we conducted a regression-based form of the classic Hausman test proposed by Wooldrige (2002) to determine whether HT adoption is endogenous.

Consider the relationship between the dependent variable $y_1$ and the independent (but potentially endogenous) variable $y_2$. To test the exogeneity of $y_2$, Hausman (1978, 1983) suggests a simple two-stage procedure: 1) regress $y_2$ on a set of strictly exogenous instruments, $z$; and 2) regress $y_1$ on $z_1$ (a subset of $z$), $y_2$, and the residuals from the regression in the first stage. If the residuals from the first stage are significant in Stage 2, then unobserved factors affect both $y_1$ and $y_2$. In other words, $y_2$ is endogenous.

Using 1996-2006 as our sample period, we tested whether state-level HT adoption was exogenous to 1) state-level conservation tillage rates and 2) quality-adjusted herbicide use. We used the lagged soybean price, lagged herbicide price, weather variables (temperature and precipitation during plant growing season), and an indicator for weed resistance as instruments in a two-way fixed effects model (first stage that included year and state fixed effects). As described earlier in this section, we used this regression to calculate residuals. These residuals act as a proxy for unobserved, omitted, and potentially endogenous variables.

Notice that the residuals from HT soybeans equation were not statistically significant in either the conservation tillage or the quality-adjusted herbicide equation (Table A3).[9] This allows us to conclude that state-level HT soybean adoption rates are exogenous to state-level tillage rates and state-level quality-adjusted herbicide use for the 1996-2006 period. Consequently, our model can be estimated as a recursive system.

9. *The full regression results are available upon request to the authors.*

**Table A4. Hausman test results for random/fixed effects.**

| $H_0$ = Both the random and fixed effects estimators are consistent[1] | | |
|---|---|---|
| **Dependent variable** | **Test statistic** | **P-value** |
| **Conservation tillage** | 0.31 | 0.86 |
| **Quality-adjusted herbicide use** | 1.28 | 0.87 |

*[1] The random effects estimator is efficient, so failure to reject the null hypothesis serves as justification to use the random effects estimator.*

*Source: Model results*

## Appendix 4. Estimating and Testing for Fixed and Random Effects

Using Baltagi's notation (Baltagi, 2001), the fixed effect model is

$$Y_{it} = \alpha + X'_{it}\beta + u_{it}, \quad i=1\ldots N; \; t=1\ldots T \qquad \text{(A1)}$$

$$u_{it} = \mu_i + \lambda_t + v_{it}, \qquad \text{(A2)}$$

where $i$ represent states and $t$ denotes time (year), $\alpha$ is a scalar, $\beta$ is Kx1, and $X_{it}$ is the observation for State $i$ in time $t$ for the $K$ explanatory variables. $\mu_i$ is the unobservable individual specific effect; it is time invariant and accounts for any individual effects not included in the regression (Baltagi, 2001). $\lambda_t$ 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 $\mu_i$ and the $\lambda_t$ are assumed to be fixed parameters to be estimated. The $X_{it}$ is assumed to be independent of $v_{it}$ for all $i$ and $t$ (Baltagi, 2001). For the random effects model, the $\mu_i$ and $\lambda_t$ are assumed to be random and independent of the $v_{it}$ ; $X_{it}$ is assumed to be independent of $\mu_i$ , $\lambda_t$ , and $v_{it}$ for all $i$ and $t$ (Baltagi, 2001).

To estimate the models we used the PANEL procedure from SAS (2010). Fixed effects models include dummy variables that correspond to the specified state and time effects. For random effects, we employed a two-stage approach. In the first stage, we estimated the error variance components as per Fuller and Battese (1975). In the second stage, we used the estimated variance components to perform the GLS regression.

To choose between the fixed effects and random effects models we used a Hausman test. In this test, the null hypothesis ($H_0$) is that both the random effects and the fixed effects estimators are consistent. We tested the null hypothesis that both estimators are consistent by determining whether the two estimators are significantly different from each other. The Wu-Hausman test statistic is defined as $(b_1 - b_0)'\,[\mathrm{Var}(b_0) - Var(b_1)]^{-1}\,(b_1 - b_0)$. Asymptotically, the statistic is chi-squared distributed, with degrees of freedom equal to the rank of matrix $Var(b_0) - Var(b_1)$.

As seen in Table A4, $H_0$ cannot be rejected. Thus, the Hausman test allow us to conclude that both the random effects and the fixed effects estimators are consistent in both equations (p = 0.85 for the conservation tillage adoption equation and p = 0.86 for the herbicide quantity equation). Because random effects models are more efficient than fixed effects models, we have chosen a random effects model to analyze our dataset.